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Who Benefits the Most from Micro-Credit? Micro-Level Evidence from Sub-Saharan Africa

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ABSTRACT

This paper moves beyond typical mean effect analysis to examine who truly benefits from micro-credit. Utilising household-level panel data from 2010 to 2019 for a sample of Sub-Saharan African countries, via a quantile panel framework, we show that micro-credit has positive outcomes for households below specific welfare levels in low and lower-middle income countries. Conversely, the impact is less pronounced for wealthier households. Our results highlight inequalities in welfare outcomes, particularly favouring households in low to median quantiles. Notably, the effects of micro-credit vary across countries' welfare levels, with significant impacts observed in low income countries. Policy recommendations emphasise targeting micro-credit interventions towards low to median welfare households to enhance welfare outcomes.

1. Introduction

The evidence on the impact of micro-credit has spanned from determining whether micro-credit has a positive effect on welfare (Attanasio et al., 2015; Banerjee et al., 2015; Regasa et al., 2021; Van Rooyen et al., 2012), to whether credit has a dampening effect (Chen & Ravallion, 2010), and if credit has any significant effect at all on welfare (Angelucci et al., 2015; Banerjee et al., 2015). Other studies focus on different outcome measures and the impact of micro-credit on either aggregate measures or sub-aggregate measures (Akotey & Ajasi, 2016; Angelucci et al., 2015)). While the divide on the evidence in the literature exists for both developing and developed economies, an important gap, yet to be answered, is to whom should policy makers and development organisations divert finance to enhance welfare? Should governments restrict credit to certain households and improve the proportion of credit provided to others? And what could be the aftermath of those policies on welfare?

The principal contribution of this paper is to attempt to provide answers to the question regarding who should receive micro-credit in relation to the effects of micro-credit on the poor? Put differently, this work attempts to answer the question on whom among the poor does micro-credit impact most? Micro-credit in this case is obtained from formal and semi-formal sources. We take into consideration the credit market in both low and lower-middle income Sub-Saharan African countries, characterised by imperfect credit market environments (Chancel et al., 2022; Ismi, 2004), and evaluate the effect of obtaining credit on various levels across the distribution of household welfare for a number of welfare indicators. This is because the effect of credit on a welfare level might not be the same for all and thus heterogeneity within households might lead to heterogeneous effects of micro-credit on welfare. This study thus provides new evidence in the micro-finance literature to answer the question on where governments should divert finance to and the implications for welfare within both low and lower-middle income countries.

Previous studies assume that households have the same average welfare levels, and thus have relied on mean effect analysis to assess the impact of micro-finance programs (Asad et al., 2015; Attanasio et al., 2015; Dimova & Adebowale, 2017; Liqiong et al., 2019). However, as our study shows, this may not be true as households who apply for credit have varying welfare levels. Thus, in this work, by examining beyond the mean level effects of credit on welfare, we show that credit

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could have heterogeneous impacts on welfare outcomes depending on the welfare level of those who obtain credit. Given the perceived importance of micro-credit in alleviating poverty (MIX, 2011; Yunus, 1998; Yunus & Heiden, 2019), our contribution is unique as it provides new arguments to the literature by examining the variations among poor households that truly benefit from micro-credit and by identifying their welfare improvements as a result of micro-credit. This is crucial for ensuring finance optimisation regarding improving living conditions in low and lower-middle income countries.

This paper employs a quantile regression econometric framework that enables us to examine the effects of obtaining credit on various distributions of welfare using three waves of a household-level panel dataset spanning over the period 2010 to 2019 for lower-middle and low income countries in Sub-Saharan Africa. Our quantile estimation approach, in a panel data setting, allows us to account for endogeneity stemming from unobserved heterogeneity and the effects of heterogeneous covariates. In addition, the use of panel data offers the opportunity to introduce fixed effects, additionally controlling for unobserved covariates. Specifically, we use the Machado and Santos Silva (2019) quantiles via moments approach and complement our analysis using the modified (Canay, 2011) 2-step quantile approach, proposed by (Rios-Avila & Maroto, 2024), for robustness. Both methods account for the intersection of unobservable bias and heterogeneous covariates effects in a similar way to the GMM and IV methods respectively.

The results from our analysis reveal that obtaining micro-credit has positive implications for households below certain welfare levels in both low and lower-middle income countries. However, richer households experience minimal impacts from financial credit. Specifically, the results indicate inequalities in welfare outcomes due to obtaining credit, with significant effects for households at the low to median quantiles of the distribution. The impact of credit shows significant heterogeneity, with substantial effects in countries with lower welfare levels, while being negligible in countries with higher welfare levels relative to their counterparts. Additionally, in low income countries, households tend to use obtained credit for short-term welfare measures, such as consumption per capita, food, and non-food measures, rather than long-term investments. In lower-middle income countries, however, positive effects on long-term welfare indicators, like education, are observed mainly for median and slightly below median welfare households. Our results remain robust across alternative welfare indicators, estimation methods, and empirical specifications.

The rest of the paper is structured as follows. Section 2 provides a literature review on micro-credit and welfare. Section 3 provides the methodology employed in the study, while Section 4 provides insights on the data used. Next, Section 5 presents the empirical results. Finally, Section 6 presents our conclusions and the policy implications.

2. Literature review

The focus of the micro-finance literature has seen controversy on the impact of micro-credit on various welfare measures, with differences also found in association with context diversion, and short-term or long-term impacts. However, there is no evidence, that we know of, that has focused on who should get micro-credit and the consequent effect on welfare as well as the implication of restricting credit on distributional basis for certain households while improving the same for others. At best, studies have focused on certain observable characteristics of households who get micro-credit from suppliers (supply side issues) or features of households who either apply or stalled their application for micro-credit due to certain risk factors which are basically demand side issues (see, for example, Akotey and Ajasi (2016), Asad et al. (2015) and Dimova and Adebowale (2017)).

One trend in the literature has argued that micro-credit possesses a significant impact on the poor (Asad et al., 2015; Attanasio et al., 2015; Liqiong et al., 2019) as compared to works which argue that credit has instead a dampening effect, or even questions whether credit possess any significant effect at all on welfare (e.g., Hulme & Mosley, 1996; J. et al., 2001; Morduch, 1998; Mosley & Hulme, 1998; Zaman, 2001). Others suggest it does not significantly raise income, or has a mixed effect (Banerjee et al., 2015), or that it does not empower women (e.g., Husain et al., 2014; Mayoux, 1999; Rahman, 1998). Some argue that a single financial credit intervention is not enough (Lipton, 1996) and others portend the negative effects of financial credit showing evidence that financial credit does more harm because it raises inequality, increases financial services discrimination, increases workload and child labour, and raises dependency (Adams & Von Pischke, 1992; Copestake, 2002; Rogaly, 1996). Other studies focus on aggregate measures or sub-aggregate measures and endogeneity problems (Akotey & Ajasi, 2016; Angelucci et al., 2015; Dimova & Adebowale, 2017). A question that has been left unanswered is what level of poverty should be considered if poor households are to receive credit? And in what type of countries are these arguments valid?

Moreover, other studies focus on the relevance of who supplies credit and show that micro-credit from Non-Governmental Organisations could be relevant depending on the economic conditions of households as compared to micro-credit interventions from governments (Chavan & Ramakumar, 2002). The argument was premised on the evidence of Yunus (1998) that formal lenders often ignore unbanked households due to high transactional cost of monitoring loan usage and determining the credit worthiness of those households. A shift in literature has also focused on gender and discrimination in terms of obtaining loans. The literature has been evolved on how gender influences the accessibility of credit (Ghosh & Vinod, 2017; Mazumder et al., 2017; Salgado & Aires, 2018; Wahidi, 2017), some scholars contend that women face credit supply discrimination not solely based on gender but rather due to the perceived less robust nature of their projects (Bellucci et al., 2010; Brana, 2013; Leach & Sitaram, 2002). Further research backing the loan-demand premise suggests that debt aversion mostly characterises female entrepreneurs because of their higher risk aversion compared with males (Carter et al., 2007; Dawson & Henley, 2015).

Another direction of argument is schemed to answer the question on whether micro-credit can lead to long-run development in the establishment of business start-up rather than the anti-poverty tool as argued by other authors. Ahlin and Jiang (2008) present findings on the enduring impacts of micro-credit within a model of occupational choice, similar to Banerjee and Newman (1993). They argue that the sustained effects of micro-credit are influenced by the simultaneous facilitation of micro-saving and the eventual graduation of the average borrower. They propose that the emphasis should be on accumulating sufficient wealth for full business start-ups, rather than indefinite retention. This, they suggest, should be the goal of micro-banks, for micro-credit to serve as a steppingstone to broad-based development, rather than merely an anti-poverty tool. Furthermore, studies such as Matsuyama (2007) offer evidence that enhancements in the credit market, which increase access to non-frontier technologies, may reduce long-run efficiency. Matsuyama (2006) explores the impact of introducing a moderately productive self-employment technology on a range of potential steady states and concludes that self-employment may either raise or lower long-run income levels.

Furthermore, Aitken (2013) provides an argument on the financialization of micro-credit. The study argues that financialisation techniques such as valuation, intermediation and securitisation are used to turn micro-credit into a commercial process. Additionally, credit suppliers, especially banks, follow a credit rational criterion to link credit score, interest rates and other risk factors to decide who gets loans. Although Waller and Woodworth (2001) show that micro-credit can be identified as a grass-root policy for third world countries at the inception of the arguments on the impact of credit on economic indicators, a few other studies have also argued in favour of protecting borrowers. For instance, Fernando (2006) argues that imposing ceilings on micro-credit interest rates could hurt both the poor and credit suppliers.

Following the trend of arguments in the economics-finance literature on the impact of credit on welfare, we deem it necessary to go beyond the impact of micro-credit on the welfare levels of the poor on a general basis, as well as, a mean effects level. We propose that greater evidence on who really should get finance provides important evidence for governmental and developmental agencies as regards micro-credit and welfare improvement. This is because not everyone who applies for credit really needs credit or may not be able to use it in the best way, and the effects on improving welfare may vary depending on the welfare level of those who receive credit. It is on this basis that we attempt to provide answers on who should really get micro-credit from formal and informal institutions. This analysis deviates from the usual mean effect regressions in literature to provide evidence on who benefits most from micro-credit.

3. Methodology

To answer the question in this paper, which considers whether there is variation in the relationship between financial credit and welfare by the nature of the household, we adopt a quantile regression methodological approach. The aim is to identify the varying levels of welfare across households to see if financial credit policies have any effect across these different levels, and through this, to determine who benefits most from financial credit in terms of welfare. We, thus, follow a quantile estimation approach, which is particularly useful with panel data models to account for endogeneity stemming from unobserved heterogeneity and the effects of heterogeneous covariates. In addition, the presence of panel data offers the opportunity to introduce fixed effects, aiding in the control of certain unobserved covariates.

Currently, a growing body of evidence is emerging on the intersection of these two methodologies (e.g., Abrevaya & Dahl, 2008; Canay, 2011; Galvao, 2011; Geraci & Bottai, 2007; Koenker, 2004; Lamarche, 2010; Machado & Santos Silva, 2019; Rosen, 2012), however, in our work, we use the Machado and Santos Silva (2019) approach of quantiles via moments and complement our analysis with the modified (Canay, 2011) 2-step estimator approach. The Machado and Santos Silva (2019) quantiles via moments approach allows for robust estimation of quantile effects in the presence of endogenous explanatory variables, similar to the one-step GMM, and produces more efficient estimates when compared to the IV quantile regression approach (see Machado & Santos Silva, 2019). The modified (Canay, 2011) 2-step estimator approach accounts for the intersection of unobservable bias and heterogeneous covariates effects, and works very similar to the IV method, but addresses endogeneity using a control function approach.[1]

We start by specifying the following panel regression model,

$$y_{ict} = x'_{ict}\beta(u_{ict}) + \eta_i, \tag{1}$$

for $i = 1\ldots,n$ households, $c = 1,2,3,4$ countries, $t = 1\ldots,T$ years and $(y_{ict},\ x_{ict}) \in \mathbb{R} \times \mathbb{R}^k$ are observable variables with y_{ict} depicting the welfare indicators while x_{ict} represents the controls among which includes the main dependent variable of interest (financial credit) and the unobservable components are $(u_{ict},\ \eta_i) \in \mathbb{R} \times \mathbb{R}$. The vector x_{ict} is assumed to include a constant term, i.e., $x'_{ict} = (1,\ x^{s\prime}_{ict})$ with $x^s_{ict} \in \mathbb{R}^{k-1}$. The function $\tau \mapsto x'\ \beta(\tau)$ is assumed to be strictly increasing in $\tau \in (0,1)$ and the parameter under consideration is assumed to be $\beta(\tau)$ which denotes the conditional quantile effect of an independent variable on an outcome variable of interest at τ-quantile, given some covariates. If η_i were observable it would follow that

$$P[y_{ict} \le x'_{ict}\beta(\tau) + \eta_i | x_i, \eta_i] = \tau_i, \tag{2}$$

under the assumption that $u_{ict} \sim$ u[0, 1] conditional on $x_i = (x'_{i1}, \ldots . x'_{iT})$ and η_i. Particularly, this representation has been extensively used in the literature (e.g. Chernozhukov & Hansen, 2006). However, the notable distinction between the model specified in Eq. (1) and the conventional quantile regression model introduced by Koenker and Bassett (1978) is in the inclusion of the unobserved η_i. This variable which is random may be arbitrarily related to other random variables in Eq. (2) (i.e., $\eta_i = \eta_i(u_{it},\ x_i,\ \gamma_i)$ for some i.i.d. sequence (γ_i) rendering condition (2) as not particularly useful in terms of identification.

Consequently, a critical question what answering is under what additional conditions the unobservable variables $(u_{ict},\ \eta_i)$ with the parameter $\beta(\tau)$ can be identified and consistently estimated from the data, as Rosen (2012) demonstrated that conditional on covariates, quantile restriction in isolation will not identify $\beta(\tau)$ due to insufficient identification power. Various authors have explored options around this problem,[2] however, we adopt here both the Machado and Santos Silva (2019) method and the modified (Canay, 2011) method, as proposed by Rios-Avila and Maroto (2024), that account for endogeneity from unobserved heterogeneity, for heterogeneous covariates effects and for fixed effects to control for unobserved characteristics through the availability of panel data. We, thus, follow these approaches because they best suit the data available and also improves on some of the approaches explored earlier.

First, for our main analysis, following Machado and Santos Silva (2019), we estimate the conditional quantiles $Qy(\tau|x)$ for a location-scale model of the form

$$y_{ict} = \eta_i + x'_{ict}\beta + (\delta_i + z'_{ict}\gamma)U_{ict}. \tag{3}$$

With $Pr(\delta_i + z'_{ict} > 0) = 1$. The parameters (η_i, δ_i), $i = 1,\ldots,n$, capture the individual i fixed effects and z is a k-vector of known differentiable (with probability 1) transformations of the components of x with element l given by $zl = zl(x), l = 1,\ldots,k$. The sequence x_{ict} is strictly exogenous, i.i.d. for any fixed i, and independent across i. U_{ict} are i.i.d. (across i, c and t), statistically independent of x_{ict}, and normalised to satisfy the moment conditions where $E(U) = 0 \quad E(|U|) = 1$.

Model (3) implies that

$$Qy(\tau|x_{ict}) = (\eta_i + \delta_i q(\tau)) + x'_{ict}\beta + z'_{ict}\gamma q(\tau). \tag{4}$$

Machado and Santos Silva (2019) refer to $\eta_i(\tau) \equiv \eta_i + \delta_i q(\tau)$ as the scalar coefficient which is the quantile-τ fixed effect for individual i, or the distributional effect at τ. The distributional effect differs from the usual fixed effect in that it is not, in general, a location shift. That is, the distributional effect represents the effect of time-invariant individual characteristics which, like other variables, are allowed to have different impacts on different regions of the conditional distribution of y. The

[1] The Canay (2011) 2-step estimator addresses the problem of unobservable fixed effects in panel quantile regressions through a two-step process. In addition, this method helps to circumvent endogeneity problems using a control function approach similar to an IV-2SLS. Finally, it is suitable for both small and large panels, making it compatible with our data. The control function approach addresses endogeneity issues similar to a 2SLS method through the addition of the fitted residuals of the first-stage regression as an additional regressor into the main regression model (second-stage). Wooldridge (2010) shows that the 2SLS and control function (CF) approaches give identical estimates for the regression parameters in the linear regression model. The idea here is that the fitted residual term captures the omitted variables that make the main independent variable endogenous. By including this term, we control for endogeneity issues.

[2] Some of the approaches explored in the literature are the panel method with individual fixed effects of Galvao (2011), the instrumental variable approach of Chernozhukov and Hansen (2006) and Galvao (2011), the fixed effect penaliser of Koenker (2004), the non-additive fixed effects of Powell (2022), the quantiles via moments of Machado and Santos Silva (2019), and the 2-step approach of Canay (2011), among others.

moment conditions MM-QR estimator of Eq. (4) takes a convenient triangular structure with respect to the model parameters that allows the one-step GMM estimator to be calculated sequentially (Machado & Santos Silva, 2019). For our complementary analysis, Canay (2011) also resolves the identification conditions problems for unobservable variables (u_{ict}, η_i) by following a simple data transformation that eliminates the fixed effects η_i as $T \Rightarrow \infty$ (as time increases). The transformation leads to an extremely simple asymptotically normal estimator for $\beta(\tau)$ that can be easily computed even for very large values of n-observations. To address this identification issue, we follow the 2-step estimator approach of Canay (2011) similar to the IV estimation method. The 2-step estimator exploits two direct implications and the fact that η_i is a location shift. This gives a conditional mean equation for y_{ict} below as:

$$y_{ict} = x'_{ict}\beta_\mu + \eta_i + U_{ict}, \quad E[U_{ict}|x_i, \eta_i] = 0. \tag{5}$$

Eq. (5) implies that η_i is also present in the conditional mean of y_{ict}. However, the Canay (2011) estimator assumes that the model error in Eq. (5) is homoscedastic with respect to the individual effect η_i. If this is the case, a consistent estimator for the parameter $\beta(\tau)$ for each τth conditional quantile can be obtained using a two-step procedure. Studies like Besstremyannaya and Golovan (2019) have also shown that the analytical standard error derivations by Canay (2011) could be incorrect.

Hence, following Rios-Avila and Maroto (2024), we use the modified (Canay, 2011) approach which incorporates bootstrap resampling methods to the standard errors of the basic (Canay, 2011) estimator. Consequently, from Eq. (5), using bootstrap standard errors, a $\sqrt{T}$ -consistent estimator of η_i is computed by using a $\sqrt{nT}$ -consistent estimator of β_μ following Canay (2011). Afterwards, one can estimate $\beta(\tau)$ by a quantile regression of the random variable $\hat{y_{ict}} \equiv y_{ict} - \hat{\eta_i}$ on x_{ict}.

In more simple terms, the 2-step estimator is defined as follows.

Step 1. Let $\hat{\beta_\mu}$ be a $\sqrt{nT}$ - consistent estimator of β_μ. Where the parameter $\hat{\eta_i}$ is defined as $\hat{\eta_i} \equiv E_T[\hat{y_{ict}} - x'_{ict}\ \hat{\beta_\mu}]$.

Step 2. Let $\hat{y_{ict}} \equiv y_{ict}$ - $\hat{\eta_i}$ and the two-step estimator $\hat{\beta(\tau)}$ as:

$$\hat{\beta(\tau)} \equiv \arg\min_{\beta \in B} E_{nT}[\rho_\tau(\hat{y_{ict}} - x'_{ict}\hat{\beta})]. \tag{6}$$

The definitions in step one and two can be simply summarised as estimating a first stage fixed effects regression model of independent variables on the outcome variable of interest. After that a control function approach is used to account for unobservable factors by generating the predicted value of the outcome variable from the estimated model and subtracting the predicted value from the actual value of the outcome variable (similar to an IV estimator). Then a second stage conditional quantile regression is estimated.

4. Data

This study employs the World Bank General Household Survey (GHS) household-level panel dataset using three waves from 2010 to 2019 for four Sub-Saharan African countries, grouped into low income and lower-middle income groups. The countries are Nigeria and Tanzania, which are classified as lower-middle income countries, while Ethiopia and Malawi are classified as low income countries according to the World Bank classification (World Bank, 2022).[3] The intuition for selecting these countries is to capture Sub-Saharan African countries with large credit markets as well as based on availability of data. Also, these four countries are characterised with high levels of inequality, see Chandy and Seidel (2017). We thus use this fact to show that credit could have different impacts on welfare depending on the welfare levels of those who apply, instead of assuming average welfare levels for all households and estimating mean effects.

The World Bank GHS dataset contains about 4900 households for Nigeria, 3969 for Ethiopia, 3000 households for Malawi and for 1200 households for Tanzania and across a panel period from 2010 to 2019. Welfare indicators in terms of consumption per capita, education, food and non-food expenditures are included in the dataset.[4] We use a binary variable for micro-credit that equals one for households who have applied for loans and actually received the loans and zero if households did not receive loans, whether they have applied for loans or not. The measure of credit here is thus restricted to only those households who have received credit and not those whose applications are pending, as the data do not provide the information as to whether the loans were received at later periods in that year. Furthermore, this is done to assess the true impact of those who really obtained credit versus those who did not. From the dataset across the four countries, 6670 (19.13%) households indicated that they obtained loans, while 28,199 (80.87%) indicated that they did not.

The data also contains information on sex of household heads, employment status, religion, as well as the distances to market, population centre, capital, border to indicate the location of households, and climatic factors as latitude, rainfall and the wetness of land for accessibility to road or other transportation. Other controls are marital status and, whether household heads interviewed can read and write. Hence, following data availability, we include demographic features of households like sex of household head that highlights information on the leadership responsibility in each household; whether households can at least read and write in English which depicts their basic education level required for most loan applications; employment status to provide insights on their economic conditions and marital status to highlight their social class. Many welfare economists argue that paid employment contributes significantly to improving welfare conditions of households (Otaki, 2009), hence we expect that generally, those who are employed should have better welfare levels. Religion is included in our dataset following the arguments from studies that show the significant role of religion on welfare (see Dehejia et al., 2007; Dills & Hernández-Julián, 2014). Specifically, we have included this variable as a dummy (that equals one if Christian and zero otherwise) for two reasons. First, in our dataset, about 64% percent of the households are Christians. Second, due to the dominant nature of the two main religions (Christianity and Islam) in the African continent. Specifically, the two major religions in Africa are Christianity and Islam with nearly 49% of the continent's population are Christians and 42% are Muslims (Centre for Study of Global Christianity, 2020).

Furthermore, we include regional trade and commercialisation factors in the literature that are important to welfare like distance to markets, distance to nearest road, distances to nearest border and distance to capital centres. Studies like Ali et al. (2014) and Mukasa et al. (2017), highlight the importance of these factors. Generally, poorer households are associated with farther distances to these areas of commercialisation and trade.

Acemoglu et al. (2001) and Hall and Jones (1999) document the correlation between distance from the equator, like latitude, and wetness of land with economic development. Following these studies, we also include climatic and regional factors such as latitude and wetness of land in our analysis. Whilst wetness of land highlights the topography of household locations which could be central to accessibility and transportation, latitudes can be used to capture seasonal climatic changes in regions. For instance, in higher latitudes, the seasons are more distinct. Summers can be warm, while winters tend to be cold and

[3] We follow the World Bank classification where countries with per capita income is 12,376 US Dollars or above are classified as high income countries, countries with per capita income between US 1026 to 3995 US Dollars as lower-middle income economies and countries with per capita income below 1025 US Dollars are classified as low income countries.

[4] We have also explored other country specific welfare measures which are available in the dataset for some of the countries but absent in others. These additional findings are available from the authors upon request.

Table 1
Summary statistics for continuous variables.

Variable	Obs	Mean	Std. Dev.	Min	Max	Quantiles				
						10	25	50	75	90
Tot. cons	21 719	282.417	385.646	0.0	24 033.92	1.870	67.462	195.355	379.403	630.571
Ed. exp	26 363	41.063	136.214	0.0	8729.973	0.0	0.323	6.986	35.644	100.51
Fd. exp	27 493	220.301	415.906	0.0	23 961.7	0.01	0.018	107.695	272.367	528.596
Non fd. exp	26 309	128.009	327.225	0.0	25 111.11	14.526	32.739	74.862	148.318	262.357
Latitude	33 164	4.24	9.639	−16.986	67.88	−14.208	1.875	7.276	10.0245	12.420
Rainfall	33 164	966.404	376.647	247	2537	563	718	848	1179	1488
Wetness	33 165	181.646	443.184	11	1147	9	13	17	18	913
Dist-Popcenter	33 164	41.198	39.356	0.0	259.03	4.1	13	30.4	55.3	92
Dist-Market	34 139	258.839	463.139	0.0	2560	4	12.9	62	183.8	1032
Dist-Border	33 164	257.192	225.03	0.0	1110	26	65.7	203.8	394.6	588
Dist-Capital	33 164	256.507	452.507	0.0	2574	10	18	68.4	210.6	1008

Notes: All expenditures have been converted to US Dollars using the official exchange rate for each country. The distance is reported in kilometres.

severe. In regions near the equator, both daylight and temperature remain relatively stable throughout the year and the consensus is that the potential for crop yield reduction is greatest in warmer, lower latitude areas and semi-arid areas of the world (Rosenzweig & Iglesias, 1994). Furthermore, Desmet and Rossi-Hansberg (2015) argue that warming activities differs across different latitudes which in turn affects various economic activities like productivity, trade and welfare. In addition, Hamermesh et al. (2006) argue that latitude of regions could affect coordination which is central to economic activities and behaviour, while Pawliczek et al. (2022) find that latitude is positively associated with welfare. Moreover, we include rainfall which is another climatic factor relevant to welfare. Whilst the literature argues that moderate rainfall improves productivity for households (Björkman-Nyqvist, 2013; Maccini & Yang, 2009; Rocha & Soares, 2015), harsh rainfall conditions from adverse climate change situations can also contribute to erosion, poor roads and transportation and adverse welfare conditions (Chang, 2002).

For the welfare indicators, we use some established welfare measures in the literature like total consumption per capita, education expenditure per capita, food expenditure and non-food expenditures following studies such as Ghalib et al. (2015), Mukasa et al. (2017) and Regasa et al. (2021) amongst others. Total consumption measures the average quantity of goods and services consumed by each household in the panel and is a crucial economic indicator as it provides a clear picture of individual consumption patterns. Education expenditure measures the human capital development of individuals or households which is again an important welfare indicator (Appiah & McMahon, 2002). Food expenditure measures the total money spent on food both for home consumption and out-of-home food purchases. Food consumption and expenditure underpin the most widely used measures of poverty and of food security, and assessment and monitoring of the well-being of any human population especially some of the targets set for Sustainable Development Goals 1 and 2 (ending poverty and hunger). Similarly, data on food expenditure are needed to assess and guide the mandate of FAO 2016 to help eradicate hunger, food insecurity, and malnutrition. Non-food expenditures are the costs of goods and services that are not food-related, such as: soap, transport, airtime, clothing, kitchen equipment, etc.

Given that we use micro-data collected in waves, it is not possible to obtain real measures of food and non-food expenditures for each household in the countries included in the dataset. However, time fixed effects capture common macroeconomic trends, such as inflation, which affect all households within a given period. Since expenditures in our data are measured in nominal terms, time fixed effects are included in our model to absorb inflation-driven price increases. This helps isolate the impact of other explanatory variables on food and non-food expenditures by removing confounding effects from price level changes. The welfare measures included in our analysis are consistent with the literature as indicators of living standards (see Xu et al., 2009). A list of all variables used in our analysis and their description is provided in Table 12 of the Appendix.

4.1. Summary statistics

Table 1 presents the summary statistics for some of the variables used in the study. At this stage, basic statistics in quantiles are reported while justification for the inclusion of these variables in the analysis are provided in the preceding section. The table provides information of the distribution of the variables contained in the dataset and shows the difference between the mean welfare indicators across the entire distribution in the dataset. We do not infer any causality at this stage but show clear information to highlight what the distribution holds for all the continuous variables contained in the dataset.[5]

For consumption per capita, although the average value for households is about $282, for very poor households in the distribution it only constitutes close to $2, while for households at the 90th quantile it is about $630. It is noteworthy that amongst all the welfare indicators, households spend less on education expenditure and this we do not suppose is as a result of scholarships which are rarely given and/or difficult to justify in poor countries. This follows expectations that households in poor or lower-middle income countries see education as rather an investment when compared to other measures. Moreover, apart from total consumption per capita, households spend most on food which again follows expectations for low and lower-middle income countries. The mean level of food expenditure is about $220 with households at higher quantiles spending above $528. Next to food is the non-food expenditure in terms of how households prioritise their welfare. The information contained in Table 1 says much on what each welfare indicator means for households in low and lower-middle income countries and how households smooth their spending across the most important welfare indicators.

The summary statistics of terrain and climatic factors including latitude, wetness of land, rainfall to indicate the location of households and wetness of land for accessibility of households to road or transportation as well as access to commercialisation indicators such as distances to market, population centre, capital, and the border are also reported. For instance, the average degree distance from the equator of households in the dataset is 4.24 degrees North (latitude). We refer to studies like Asad et al. (2015) on the relevance of these variables to welfare at mean levels. The quantile reports in Table 1 help us to show in detail the dispersion from the mean in these variables across households which is important in the methodology used in this study.

Next, Table 2 presents the statistics for the micro-credit measure as well as details of households who obtained credit and those who do not. Given that the dataset contains other binary variables, we show in detail the summary statistics of the binary variables contained in the study which are basically credit status, sex, employment, an indicator

[5] In our empirical analysis, we use quantile regressions in all estimations which is robust to any possible outlier problems from extremely high(low) values (See Koenker, 2004).

Table 2
Summary statistics for credit and binary variables (by credit status).

Variable			
Credit			
Obtained	19.13%		
Did not obtained	80.87%		
	Non-financed (%)	Financed (%)	Total (%)
Male			
Female	81.42	18.58	100
Male	80.27	19.73	100
Employed			
Not employed	80.50	19.50	100
Employed	80.09	19.91	100
Married			
Not married	82.91	17.09	100
Married	79.81	20.19	100
Read			
Unable	81.56	18.44	100
Read	79.34	20.66	100
Christian			
Other	85.96	14.04	100
Christian	77.72	22.28	100

variable of whether a household member can read and write at least in English and religion. We categorise sex, employment, an indicator variable of whether household member can read and write at least in English and religion by credit status to provide richer information on the contents of the data and thus, we present the summary in percentages (%).

Table 2 show that close to a quarter (19.13%) of households obtained micro-credit finance whilst 80.87% of them did not. This highlights the credit market imperfections regarding credit constraints found in many African countries (Chancel et al., 2022; Ismi, 2004). Also, Table 2 indicates that more households are headed by males. Nearly 20% of male headed households obtained loans, while about 19% of women headed households obtained loans. Although, several works have argued about the risk averse nature in borrowing by women, we, at this point, make no claims on this argument as the data does not show why women did not receive or apply for loans. Probing further into the data, show that nearly an equal percent of both employed and unemployed households in low and lower-middle income countries obtain financial credit, approximately (20%). Moreover, as expected, more of those who can read and write obtained credit (20.66%) while more Christians applied for and obtained loans (22.28%).

4.2. Selecting controls

Here we highlight relevant controls included in the analysis as regards welfare at mean level (Ghalib et al., 2015).[6] Specifically, these controls are important factors to consider especially for rural or poor households in developing countries. As discussed previously, we include demographic factors like sex, employment and marital status, religion, and whether the household head can read and write, as well as distances to market, population centre, capital and border, and climatic factors as latitude, wetness of land and rainfall. While there are other individual country specific factors that are prevalent in the different countries, we include only factors that are consistent and available in the dataset for all countries. Although there may be some other characteristics not included in our controls (e.g., entrepreneurship), as in Mazumder et al. (2017), we aim to avoid issues arising from

[6] For more details, see the paper of Ghalib et al. (2015). In that work, they include a number of factors that proxy distance of households to market, primary form of education, terrain of households, sex, religion, employment status, similarly to our study.

Table 3
Controls and determinants of welfare.

	Tot. Cons	Ed. Exp	Fd. Exp	Non Fd. Exp
Male	21.17	2.551	39.26***	3.247
	(11.12)	(2.615)	(8.393)	(5.748)
Employed	2.352	−17.42***	3.828	−8.284*
	(8.025)	(1.595)	(5.119)	(3.506)
Married	173.8***	−2.092	117.5***	27.05***
	(11.13)	(2.523)	(8.097)	(5.545)
Read	57.04***	3.226	18.05***	25.18***
	(7.252)	(1.646)	(5.283)	(3.618)
Christian	19.17	1.818	1.350	17.27*
	(12.82)	(3.102)	(9.956)	(6.818)
Latitude	1.942	0.648**	0.506	0.0558
	(1.080)	(0.228)	(0.731)	(0.501)
Rainfall	−0.139***	−0.0166	−0.0568*	−0.0515**
	(0.0405)	(0.00879)	(0.0282)	(0.0193)
Wetness	2.316	−0.0117	−0.0172	−0.0573
	(3.536)	(0.0148)	(0.0474)	(0.0324)
Dist-Popcenter	0.337*	−0.0372	0.115	0.0839
	(0.146)	(0.0260)	(0.0834)	(0.0571)
Dist-Market	−0.0729**	0.0222***	−0.0258	−0.0545***
	(0.0259)	(0.00513)	(0.0165)	(0.0113)
Dist-Border	0.0382	0.0396**	0.0163	−0.0391
	(0.0677)	(0.0132)	(0.0425)	(0.0291)
Dist-Capital	0.265*	0.0917***	−0.0360	0.114***
	(0.117)	(0.0156)	(0.0501)	(0.0343)
Group FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	20 238	24 307	24 265	24 265
R-sq	0.072	0.161	0.057	0.109

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

overfitting the models with too many controls. Therefore, in addition to the relevant control variables discussed in the literature, we account for unobserved and/or omitted factors in the regression using country, group, and time fixed effects. Furthermore, in the robustness section, we examine the robustness of our results using an alternative (reduced) specification to demonstrate that our findings remain consistent and are not driven by omitted variables.

As can been seen in the panel regression with fixed effects, for all the countries used, in Table 3, the controls stated above are statistically significant determinants of welfare, for at least some of the welfare measures, except wetness of land. However, this variable is statistically significant when regressed alone on all the welfare indicators or when some of the variables in Table 3 are excluded, as shown in Table 13 in the Appendix. These results are consistent for the panel regressions at the mean level. Whether the same results are realisable for quantile regressions which address effects at various levels of the distribution of welfare is what the empirical section provides answer to. Table 3 thus summarises that these controls cannot be overlooked when assessing effects on welfare.

5. Empirical results

Tables 4 to 11 summarise the empirical quantile regression results of the impact of obtaining credit on the various distribution of the welfare levels of households at different quantiles, with all the controls shown in Table 3. The outcome of analysing the results collectively is to suggest that there are inequalities in welfare outcomes from obtaining credit. Any significant effects are particular to households that are at the low to median quantiles of the distribution for most part. Furthermore, to provide further and clearer explanation as well as clear differences on the conditional quantile regression effects of credit

Table 4
Panel quantile regressions for consumption and education (All countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	18.407***	16.788***	12.980*	5.237	2.267	1.678**	1.474	1.067	0.090	−0.360
	(5.193)	(5.154)	(7.156)	(14.525)	(18.266)	(0.805)	(1.079)	(1.267)	(2.281)	(3.198)
Male	9.273	11.640*	17.204*	28.521	32.862	2.012*	2.133**	2.376**	2.958	3.225
	(10.817)	(6.985)	(9.609)	(20.350)	(24.584)	(1.071)	(1.017)	(1.072)	(3.309)	(3.308)
Employed	5.579	4.723	2.708	−1.389	−2.961	−19.275***	−18.859***	−18.024***	−16.024***	−15.103***
	(5.627)	(5.537)	(6.434)	(16.532)	(21.905)	(2.519)	(2.326)	(2.100)	(2.218)	(2.025)
Married	93.095***	110.580***	151.700***	235.322***	267.402***	−1.386	−1.565	−1.924	−2.783	−3.179
	(10.681)	(10.181)	(12.714)	(25.559)	(31.702)	(1.173)	(1.162)	(1.316)	(2.971)	(2.966)
Read	42.803***	45.927***	53.274***	68.216***	73.948***	−1.413***	−0.356	1.762**	6.837***	9.174***
	(5.235)	(5.082)	(6.797)	(11.758)	(14.989)	(0.479)	(0.450)	(0.775)	(1.627)	(2.149)
Christian	8.065	10.330	15.658	26.493	30.650	1.166	1.298**	1.565	2.203	2.497
	(9.800)	(8.914)	(13.878)	(29.234)	(37.726)	(1.029)	(0.624)	(2.075)	(4.993)	(7.390)
Latitude	1.362***	1.485***	1.775***	2.365**	2.591	0.539***	0.563***	0.613***	0.731***	0.786***
	(0.281)	(0.279)	(0.426)	(1.040)	(1.590)	(0.191)	(0.176)	(0.201)	(0.250)	(0.274)
Rainfall	−0.051	−0.070**	−0.115**	−0.205*	−0.239	−0.002	−0.006	−0.012*	−0.029**	−0.036**
	(0.036)	(0.033)	(0.052)	(0.114)	(0.158)	(0.006)	(0.007)	(0.007)	(0.011)	(0.014)
Wetness	3.244	3.023	2.502	1.444	1.038	−0.005	−0.007	−0.010	−0.017	−0.021
	(2.709)	(2.914)	(4.117)	(8.169)	(9.660)	(0.016)	(0.017)	(0.021)	(0.035)	(0.042)
Dist-Popcenter	−0.114	−0.012	0.226	0.711	0.897	−0.029	−0.031	−0.034	−0.042	−0.045
	(0.172)	(0.159)	(0.210)	(0.511)	(0.734)	(0.023)	(0.026)	(0.032)	(0.048)	(0.054)
Dist-Market	−0.052***	−0.057***	−0.067***	−0.089*	−0.097	0.039***	0.035***	0.028***	0.008	−0.000
	(0.015)	(0.015)	(0.026)	(0.054)	(0.075)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)
Dist-Border	−0.076	−0.050	0.010	0.132	0.179	0.040*	0.040**	0.040*	0.040*	0.039
	(0.049)	(0.044)	(0.112)	(0.238)	(0.319)	(0.021)	(0.018)	(0.021)	(0.023)	(0.026)
Dist-Capital	−0.135	−0.046	0.164	0.589	0.752	0.080***	0.083***	0.088***	0.101***	0.107**
	(0.162)	(0.116)	(0.258)	(0.727)	(1.108)	(0.019)	(0.018)	(0.022)	(0.033)	(0.043)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

on the various welfare measures, the quantile regression plots are also presented. These are reported in Figs. 1 to 3.[7]

5.1. Main results

Specifically, the main results, based on the Machado and Santos Silva (2019) quantile estimator, are presented in Tables 4 and 5 and suggest that the effect of credit is very heterogeneous. Generally, what we find is that obtaining credit is more important for households at the low to median levels of the distribution of welfare as regards to consumption per capita and non-food expenditure. Thus, obtaining micro-credit improves the welfare (consumption per capita and non-food expenditure) of households in low to median quantiles when one considers both low and lower-middle African countries together. Furthermore, obtaining micro-credit improves welfare in terms of food expenditure of households in low quantiles to slightly below median quantiles.[8] With the exception of very low quantiles, micro-credit is not a sufficient measure to improving education. As the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure decreases until the median quantile, beyond which the effects of credit are not statistically significant. In contrast, we observe the opposite for non-food expenditure.

Quantitatively, the conditional quantile effect of credit on consumption per capita is \$18.40 at the 10th quantile but falls to \$12.98 at the median, before losing significance at the 75th quantile. Similarly, the conditional quantile effect of credit on food expenditure is \$8.91 at the 10th quantile and then drops to \$7.68 at the 25th quantile, before losing significance after the 50th quantile. Moreover, having a first glance in Fig. 1, one can observe that the effects of conditional quantile regression of credit is uniformly positive across all the welfare measures beginning from the low quantiles but these effects drop in magnitude as we move towards the median, with the loss of significance at the higher quantiles, as the confidence intervals clearly depict. This result is consistent across consumption per capita and food expenditure. This finding strongly confirms the point discussed above that credit has different effects at different points of the welfare distribution.

What one can infer from this result is that raising the income level of poorer households from low to around median welfare level households is very important if policy makers want to improve consumption per capita as it seems rational for these households to smooth their income more towards improving their consumption level compared to higher income level households. In corollary, what the result also suggests is that improving food expenditure seems to be a major concern for households at the lower to before median quantiles of the distribution of welfare. Thus, for these households, it is only rational to channel the credit obtained or extra income acquired to improving their food expenditure needs which is expected when considering developing countries as compared to developed ones. Available evidence prior to this study (Banerjee et al., 2015) tends to focus on the mean effect of micro-credit on welfare and show some mixed evidence. However, the mean effect approach assumes homogeneity in the welfare levels of households, however, this is not the case as even for low income countries, the distribution of welfare or poverty varies among households. The mean effect evidence from Banerjee et al. (2015) show that at mean level, micro-credit matters when consumption per capita and food expenditure is considered respectively, supporting the results in this study however, at specific quantiles. The results here show that the food needs are quite high at the lowest quantiles.

[7] In the plots we use a narrower spread of quantiles, selecting every 5th quantile and starting from the 10th to the 90th quantile, for a clearer visual examination of the impact. All the plots contain the results based on the quantile regression estimations using all the controls as shown in Table 3.

[8] Any potential inflationary trends in both food and non-food expenditures have been accounted for by including time fixed effects in the regressions.

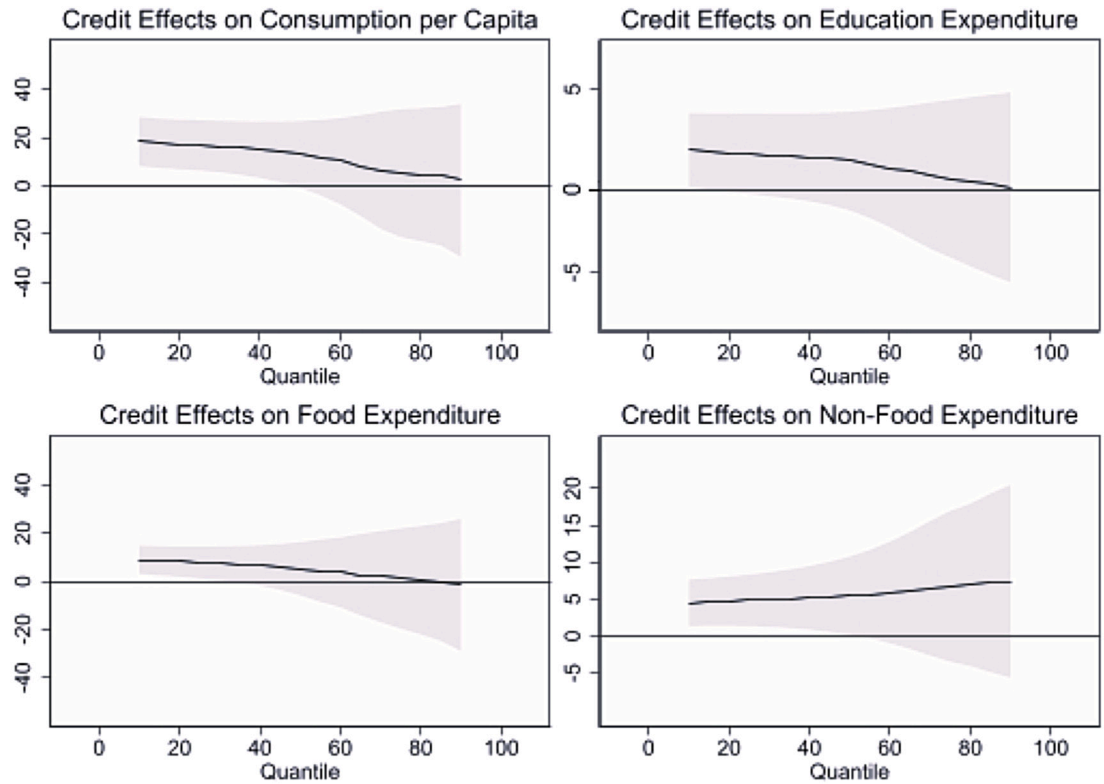

Fig. 1. Quantile regression plots of credit on welfare (All countries).

Table 5
Panel quantile regressions for food and Non food expenditures (All countries).

Variable	Fd. Exp (Food Expenditure)					Non Fd. Exp (Non-food Expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	8.911***	7.680**	5.188	1.114	−1.546	4.496***	4.831***	5.470*	6.733	7.422
	(2.759)	(3.129)	(5.550)	(11.457)	(14.743)	(1.513)	(1.426)	(2.810)	(5.568)	(8.020)
Male	17.039**	22.859***	34.644***	53.905***	66.482***	0.111	0.872	2.320	5.183	6.745
	(6.945)	(5.742)	(7.620)	(16.858)	(21.556)	(2.420)	(2.667)	(3.922)	(7.287)	(10.192)
Employed	6.163**	5.458**	4.030	1.696	0.172	−8.107***	−8.191***	−8.350***	−8.664*	−8.835
	(2.736)	(2.463)	(3.856)	(10.085)	(11.867)	(2.512)	(2.398)	(2.942)	(5.017)	(6.747)
Married	57.517***	73.725***	106.550***	160.195***	195.222***	12.359***	16.150***	23.363***	37.617***	45.398***
	(6.439)	(6.655)	(10.169)	(19.232)	(25.282)	(2.667)	(3.489)	(5.139)	(9.347)	(13.443)
Read	18.842***	18.735***	18.519***	18.166**	17.936	10.666***	14.413***	21.544***	35.633***	43.324***
	(3.255)	(3.911)	(5.104)	(9.258)	(14.027)	(1.686)	(1.599)	(1.959)	(4.227)	(6.464)
Christian	−9.859	−7.010	−1.243	8.183	14.338	8.781*	11.034**	15.322***	23.793***	28.418***
	(10.733)	(8.821)	(11.490)	(20.398)	(30.537)	(4.717)	(4.481)	(4.876)	(8.134)	(9.895)
Latitude	0.389***	0.418***	0.477***	0.573**	0.636	−0.405	−0.285	−0.056	0.395	0.642
	(0.135)	(0.149)	(0.163)	(0.246)	(0.423)	(0.352)	(0.354)	(0.489)	(0.718)	(0.806)
Rainfall	−0.013	−0.024	−0.047*	−0.084*	−0.108	−0.032**	−0.037***	−0.047**	−0.067**	−0.078*
	(0.025)	(0.024)	(0.028)	(0.050)	(0.084)	(0.013)	(0.014)	(0.019)	(0.032)	(0.042)
Wetness	0.019	0.008	−0.013	−0.047	−0.069	−0.013	−0.024	−0.047	−0.091	−0.115
	(0.029)	(0.033)	(0.050)	(0.092)	(0.161)	(0.032)	(0.028)	(0.047)	(0.087)	(0.127)
Dist-Popcenter	−0.055	−0.008	0.090	0.248*	0.352	−0.018	0.009	0.060	0.162	0.217*
	(0.060)	(0.069)	(0.080)	(0.145)	(0.222)	(0.040)	(0.046)	(0.055)	(0.102)	(0.116)
Dist-Market	−0.021***	−0.022***	−0.024**	−0.028*	−0.030	−0.032***	−0.038***	−0.049***	−0.072***	−0.084***
	(0.008)	(0.007)	(0.010)	(0.016)	(0.027)	(0.012)	(0.013)	(0.014)	(0.019)	(0.022)
Dist-Border	−0.042*	−0.026	0.007	0.061	0.097	−0.055**	−0.051**	−0.043	−0.028	−0.019
	(0.022)	(0.019)	(0.037)	(0.074)	(0.129)	(0.026)	(0.026)	(0.038)	(0.068)	(0.102)
Dist-Capital	−0.062*	−0.054	−0.037	−0.010	0.008	0.043	0.062*	0.097*	0.166*	0.204
	(0.033)	(0.038)	(0.055)	(0.108)	(0.167)	(0.032)	(0.033)	(0.053)	(0.101)	(0.151)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 6
Panel quantile regressions for consumption and education (All countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	19.342***	16.133***	11.276***	8.602***	11.795*	1.928***	0.463***	0.127	0.180	−0.589
	(2.513)	(2.212)	(1.584)	(2.159)	(4.593)	(0.384)	(0.178)	(0.148)	(0.283)	(0.607)
Male	16.045***	18.730***	19.273***	27.005***	31.247***	1.566+	0.072	−0.077	−0.703*	−1.505
	(5.604)	(3.669)	(2.633)	(3.930)	(7.967)	(0.925)	(0.297)	(0.251)	(0.349)	(1.009)
Employed	0.592	3.779*	5.192***	6.029***	8.875***	−8.577***	−6.118***	−4.373***	−4.429***	−6.103***
	(3.515)	(1.895)	(1.388)	(1.865)	(2.996)	(1.052)	(0.524)	(0.248)	(0.245)	(0.571)
Married	167.444***	156.037***	164.691***	161.221***	166.729***	4.441***	1.956***	0.878***	−0.249	−2.107
	(5.144)	(3.052)	(2.186)	(4.294)	(7.260)	(1.074)	(0.330)	(0.266)	(0.375)	(1.342)
Read	33.186***	41.786***	51.051***	57.243***	60.830***	−3.984***	−0.609***	0.891***	3.130***	8.989***
	(2.079)	(1.707)	(1.285)	(1.552)	(2.935)	(0.434)	(0.169)	(0.144)	(0.254)	(0.665)
Christian	25.472***	22.053***	17.288***	15.535***	14.807***	−0.925*	1.224***	1.976***	3.048***	4.131***
	(2.835)	(2.443)	(1.656)	(2.516)	(4.153)	(0.398)	(0.210)	(0.170)	(0.233)	(0.586)
Latitude	2.181***	1.755***	1.696***	1.307***	1.113***	1.150***	0.688***	0.500***	0.266***	−0.053
	(0.331)	(0.144)	(0.087)	(0.128)	(0.142)	(0.069)	(0.038)	(0.024)	(0.038)	(0.088)
Rainfall	−0.118***	−0.120***	−0.125***	−0.137***	−0.138***	−0.018***	−0.016***	−0.015***	−0.011***	−0.007***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.011)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Wetness	3.164***	3.724***	2.808***	1.167+	−0.890	−0.057***	−0.051***	−0.036***	0.003	0.074***
	(0.662)	(0.488)	(0.430)	(0.673)	(1.354)	(0.002)	(0.001)	(0.002)	(0.005)	(0.009)
Dist-Popcenter	0.483***	0.476***	0.382***	0.334***	0.335***	0.009*	−0.001	0.001	−0.001	−0.013*
	(0.039)	(0.025)	(0.017)	(0.020)	(0.030)	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)
Dist-Market	−0.076***	−0.067***	−0.060***	−0.069***	−0.085***	0.011***	0.015***	0.023***	0.022***	0.023***
	(0.009)	(0.005)	(0.003)	(0.005)	(0.009)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
Dist-border	−0.046***	−0.036***	−0.001	0.052***	0.102***	0.036***	0.042***	0.044***	0.050***	0.054***
	(0.009)	(0.008)	(0.008)	(0.011)	(0.026)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dist-Capital	0.357***	0.316***	0.279***	0.256***	0.160***	0.099***	0.094***	0.092***	0.089***	0.083***
	(0.016)	(0.015)	(0.013)	(0.017)	(0.033)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252
Pseudo R-sq	0.307	0.284	0.253	0.215	0.227	0.212	0.287	0.365	0.391	0.371

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

For education expenditures however, apart from the very low quantiles, the results show no effect of credit at all for the other quantiles of the welfare distribution when one considers both low and lower-middle income countries together. This result might seem to suggest that households are smoothing their credit obtained across other welfare measures as opposed to education which they may rather see as a long-term investment. This result is also confirmed in Fig. 1 of the quantile regression plots as the confidence interval on education indicates that apart from the 10th quantile, there are no significant effects of credit on education. Interestingly, Banerjee et al. (2015) find similar results for a developing country like India, although at the mean level. This could suggest that generally, for developing countries, policy makers need to consider other policy options in combination with finance to improve education because micro-finance alone might not be a sufficient policy. Alternatively, credit in the form of tuition vouchers, tuition receipts and scholarships could be considered, rather than giving out loans in monetary forms to poor households. This is because, for these households, meeting immediate needs are prioritised over needs that are rather seen as longer-term such as education.

For non-food expenditure, the results show that there is heterogeneity in welfare outcomes as a result of obtaining credit. Although we find that credit shifts the location of the conditional welfare distribution from low to median quantile households, the results indicate that credit increases welfare dispersion between richer and poorer households. At first, the conditional quantile regression effects of credit on non-food expenditure is about \$4.49 at the 10th quantile and then is rising to \$5.47 at the median, widening the conditional welfare dispersion in non-food expenditure before losing significance, after the 50th quantile. This pattern suggests that credit has different effect on non-food expenditure for the low quantiles of the welfare distribution as opposed to the higher quantiles. Similarly, Fig. 1 makes the result easier to understand as one can observe the significant effect on low to median quantiles with a lower magnitude of the effects in the 10th quantile as compared to the 50th quantile.

5.2. Additional results

Here we present the additional results based on our complementary analysis using the modified (Canay, 2011) estimator, proposed by Rios-Avila and Maroto (2024). The results using this estimator, as shown in Tables 6 and 7, suggest again that the effect of credit is very heterogeneous. We find that obtaining credit is most important for households at lower quantile levels of the distribution of welfare in regards to consumption per capita and food expenditure, similar to the previous results based on the Machado and Santos Silva (2019). As the quantile level increases, the magnitude of the effect on both consumption per capita and food expenditure falls. Thus, like the results from the Machado and Santos Silva (2019), obtaining micro-credit reduces the welfare dispersion of households for consumption per capita and non-food expenditure when one considers both low and lower-middle African countries together. For the effect of credit on education expenditure, Table 6, we also find very similar conclusions with those based on the Machado and Santos Silva (2019) estimator, although the impact of credit extends up to the 25th quantile. Generally, the results from Tables 6 and 7 reaffirm our previous findings that apart from the very low quantiles, credit have no significant effect in higher quantiles when one considers both low and lower-middle income countries together.

However, we find a different result when non-food expenditure is considered as a welfare indicator. For non-food expenditure, the results show again that there is heterogeneity in the outcome. However, we find significant effects in all quantiles which confirms our previous point that credit has different effects at different levels of the welfare distribution. Furthermore, there is a twin-peak pattern in the magnitude

Table 7
Panel quantile regressions for food and non food expenditures (All countries).

Variable	Fd. exp (Food expenditure)					Non fd. exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	9.145***	7.871***	4.317***	3.260***	2.229	6.675***	5.979***	5.394***	5.768***	8.532***
	(1.854)	(1.348)	(0.972)	(1.134)	(1.381)	(1.628)	(0.922)	(0.941)	(1.584)	(2.872)
Male	41.803***	42.743***	42.666***	57.872***	67.182***	1.893	4.120***	2.507	2.452	7.867**
	(3.150)	(2.665)	(2.224)	(3.966)	(3.836)	(2.399)	(1.432)	(1.539)	(2.301)	(3.982)
Employed	7.720***	6.682***	7.857***	6.246***	5.094***	−7.870***	−6.464***	−5.998***	−6.312***	−10.261***
	(1.630)	(1.126)	(0.735)	(0.782)	(0.859)	(1.603)	(1.040)	(1.072)	(1.464)	(2.671)
Married	111.210***	104.854***	104.496***	95.867***	85.788***	34.126***	26.899***	21.512***	16.773***	7.315*
	(3.326)	(2.541)	(1.882)	(4.042)	(3.730)	(2.932)	(1.490)	(1.578)	(2.276)	(4.081)
Read	7.528***	10.880***	14.005***	15.625***	15.442***	4.790***	11.604***	19.717***	29.194***	43.131***
	(1.457)	(1.025)	(0.821)	(0.873)	(1.019)	(1.443)	(0.902)	(0.774)	(1.215)	(2.189)
Christian	0.131	−0.062	−1.143	−1.476	0.814	13.800***	14.197***	13.226***	16.942***	23.467***
	(1.689)	(1.451)	(1.045)	(1.273)	(1.624)	(1.384)	(1.022)	(0.969)	(1.367)	(2.522)
Latitude	0.742***	0.677***	0.533***	0.319***	0.316***	0.861***	0.400***	0.082	0.012	−0.296
	(0.152)	(0.084)	(0.064)	(0.055)	(0.053)	(0.185)	(0.105)	(0.124)	(0.212)	(0.329)
Rainfall	−0.035***	−0.036***	−0.038***	−0.046***	−0.050***	−0.045***	−0.049***	−0.050***	−0.049***	−0.051***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Wetness	−0.077***	−0.044***	−0.031***	−0.020***	−0.007	−0.148***	−0.123***	−0.090***	−0.041***	0.020
	(0.012)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.005)	(0.005)	(0.009)	(0.016)
Dist-Popcenter	0.175***	0.146***	0.104***	0.068***	0.052***	0.128***	0.091***	0.077***	0.046***	0.036
	(0.024)	(0.013)	(0.009)	(0.009)	(0.012)	(0.015)	(0.010)	(0.012)	(0.016)	(0.033)
Dist-Market	−0.023***	−0.027***	−0.028***	−0.029***	−0.035***	−0.043***	−0.031***	−0.026***	−0.030***	−0.052***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.007)
Dist-Border	−0.040***	−0.037***	−0.016***	0.019**	0.047***	−0.039***	−0.032***	−0.032***	−0.028***	−0.039***
	(0.007)	(0.007)	(0.006)	(0.009)	(0.011)	(0.008)	(0.004)	(0.004)	(0.005)	(0.009)
Dist-Capital	0.003	−0.019***	−0.022***	−0.025***	−0.034***	0.146***	0.127***	0.107***	0.095***	0.088***
	(0.012)	(0.006)	(0.008)	(0.007)	(0.008)	(0.004)	(0.004)	(0.005)	(0.006)	(0.011)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210
Pseudo R-sq	0.290	0.279	0.235	0.213	0.234	0.206	0.280	0.328	0.287	0.209

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

of the effect which suggests that credit has different effect on non-food expenditure for the low quantiles as opposed to the higher quantiles. Although we are unable to show that the magnitude and significance of the effect on non-food expenditure drops, this may be because obtaining credit can trigger commercial activities, business start-ups, further farm production activities, and more. In fact, Ali et al. (2014), show that the removal of credit constraints could improve the likelihood of households expanding their farming activities, which could lead to an increase in yields. The twin-peak pattern found here suggests that credit has different effect on non-food expenditure for the low quantiles as opposed to the higher quantiles. However, one can observe that the magnitude of this effect is largest for richer households (at the highest quantiles of the distribution) compared to poorer households, which aligns with expectations, as richer households may have other non-food priorities and investments on which they spend more.

5.3. Sub-sample analysis

As stated earlier, we probe further in to the data by separating the data into lower-middle and low income countries to see whether each sub-sample show similar or different welfare outcomes across the distribution at different quantiles. Given the limitation of the Machado and Santos Silva (2019) quantile estimator, which is less efficient for smaller panels, we use the modified 2-step quantile estimator of Canay (2011) with bootstrapped standard errors in the sub-sample analysis. The quantile regression results for the lower-middle countries are reported in Tables 8 and 9 while Fig. 2 shows the quantile regression plots.

Both Tables 8 and 9 as well as Fig. 2 show that for the lower-middle income countries, credit has significant effects on the welfare measures mainly for low to slightly above median quantiles. Put differently, financial-credit possess a positive significant implication on welfare for households not far above the median level as well as for poor households in the distribution. For consumption per capita, the conditional quantile regression effects of credit on consumption per capita only show a positive significant effect at the 10th quantile (only at 10% significance level) and the 50th quantile while other quantiles show no significant effect. This result suggest that when consumption per capita is considered as a welfare measure in lower-middle income countries, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous i.e., no inequality in welfare outcomes. This could be the case that households in lower-middle income countries are more exposed and are actually smoothing their income on other welfare indicators instead of consumption alone. This could explain why randomised control trial studies, such as Angelucci et al. (2015) and Banerjee et al. (2015) find no credit effect on consumption, especially since the mean level of welfare in India is higher than that of the countries used in this study. As the results here also confirm, credit does not improve the welfare levels of richer households. Using quantile regressions, Angelucci et al. (2015) also find no heterogeneity, although their focus was on a richer country like Mexico.

However, when education and food expenditures are considered as welfare measures in the lower-middle income countries, there is significant heterogeneity between low to slightly above median quantiles. The result in Table 8 show that the conditional quantile regression effects of credit on education expenditure is $3.84 at the 10th quantile but falls slightly to $1.99 when slightly above the median (at the 75th quantile where is significant only at 10% significance level). Again, this follows expectations as lower-middle income countries are known to have richer households who are more exposed to education as compared to low income countries. In addition, we find a similar pattern of the credit impact on food expenditure to that of education as can be seen in Table 9. We observe that the conditional quantile regression effects of credit on food expenditure is $2.35 at the 25th quantile but falls to

Table 8
Panel quantile regressions for consumption and education (Lower-middle income countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	3.776*	3.695	3.209***	2.051	0.425	3.842**	2.764***	2.730***	1.997*	2.185
	(2.191)	(2.614)	(1.087)	(1.408)	(2.576)	(1.581)	(0.787)	(0.697)	(1.097)	(1.671)
Male	34.306***	50.769***	56.283***	61.827***	80.569***	−32.551***	−32.071***	−28.826***	−22.266***	−19.295***
	(6.840)	(5.242)	(1.582)	(3.544)	(5.974)	(3.685)	(1.943)	(1.690)	(2.944)	(3.525)
Employed	18.492***	18.963***	21.874***	19.017***	17.819***	−16.013***	−18.174***	−18.058***	−19.974***	−22.924***
	(2.513)	(2.004)	(1.416)	(1.111)	(1.468)	(1.146)	(0.672)	(0.563)	(0.764)	(1.092)
Married	24.943***	9.307*	−0.319	−9.336**	−32.300***	−14.417***	−22.655***	−29.835***	−39.932***	−43.993***
	(6.694)	(5.469)	(0.599)	(3.796)	(6.436)	(3.089)	(2.075)	(1.531)	(2.787)	(4.031)
Read	13.416***	14.743***	15.504***	16.807***	17.984***	−16.188***	−10.010***	−5.727***	−2.915***	2.133**
	(1.680)	(1.608)	(0.501)	(1.002)	(1.589)	(1.088)	(0.543)	(0.566)	(0.575)	(1.034)
Christian	−0.934	−1.001	0.748	1.141	5.544*	−11.600***	−4.464***	−1.287	2.510**	7.626***
	(3.372)	(2.125)	(0.826)	(1.629)	(3.094)	(2.000)	(0.963)	(0.864)	(0.992)	(1.868)
Latitude	0.871***	0.850***	0.811***	0.546***	0.391***	0.874***	0.629***	0.451***	0.384***	0.272**
	(0.269)	(0.190)	(0.101)	(0.059)	(0.081)	(0.089)	(0.056)	(0.048)	(0.060)	(0.119)
Rainfall	0.031***	0.044***	0.046***	0.036***	0.040***	−0.059***	−0.022***	−0.007***	0.008***	0.014***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.008)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Wetness	2.089***	2.890***	2.010***	0.948**	−0.923	−0.013**	−0.018***	−0.021***	0.004	0.057***
	(0.719)	(0.641)	(0.279)	(0.432)	(1.083)	(0.006)	(0.004)	(0.006)	(0.009)	(0.015)
Dist-Popcenter	0.117***	−0.034	−0.108***	−0.182***	−0.191***	0.024*	0.024***	0.023***	0.026***	−0.008
	(0.034)	(0.027)	(0.014)	(0.012)	(0.014)	(0.013)	(0.007)	(0.007)	(0.008)	(0.016)
Dist-Market	−0.028***	−0.018***	−0.016***	−0.017***	−0.038***	0.035***	0.019***	0.016***	0.010***	0.017***
	(0.008)	(0.007)	(0.002)	(0.003)	(0.008)	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)
Dist-Border	−0.043***	−0.060***	−0.050***	−0.015*	0.014	0.052***	0.036***	0.027***	0.015***	0.004
	(0.009)	(0.008)	(0.006)	(0.008)	(0.022)	(0.010)	(0.005)	(0.004)	(0.004)	(0.005)
Dist-Capital	−0.364***	−0.383***	−0.462***	−0.424***	−0.548***	0.066***	0.060***	0.069***	0.073***	0.078***
	(0.012)	(0.019)	(0.004)	(0.014)	(0.039)	(0.006)	(0.004)	(0.005)	(0.008)	(0.013)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	8741	8741	8741	8741	8741	12 768	12 768	12 768	12 768	12 768
Pseudo R-sq	0.465	0.485	0.529	0.494	0.430	0.221	0.262	0.301	0.327	0.325

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

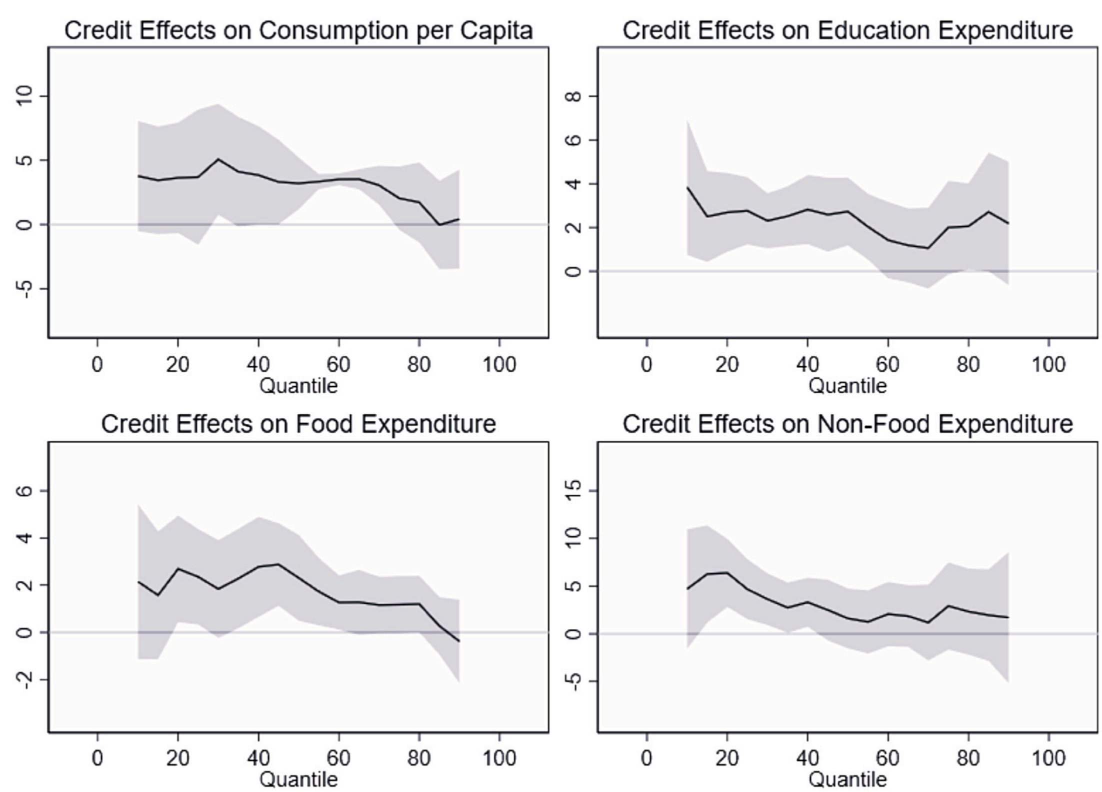

Fig. 2. Quantile regression plots of credit on welfare (Lower-middle income countries).

Table 9
Panel quantile regressions for food and non-food expenditures (Lower-middle income countries).

Variable	Fd. Exp (Food expenditure)					Non Fd. Exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	2.152	2.354*	2.309***	1.177*	−0.384	4.706	4.673**	1.614	2.923	1.705
	(1.675)	(1.209)	(0.849)	(0.683)	(0.894)	(3.203)	(1.870)	(1.697)	(2.047)	(3.343)
Male	−11.218***	−1.614	2.290	5.872***	12.014***	−72.319***	−68.591***	−60.636***	−49.004***	−36.088***
	(3.456)	(2.302)	(1.962)	(1.871)	(3.167)	(10.111)	(5.489)	(3.159)	(4.506)	(10.015)
Employed	13.174***	11.613***	11.286***	9.714***	8.777***	−10.042***	−10.653***	−10.463***	−12.477***	−16.543***
	(1.461)	(0.895)	(0.727)	(0.479)	(0.659)	(2.396)	(1.404)	(1.365)	(1.858)	(2.564)
Married	7.649**	−6.930***	−14.644***	−21.146***	−29.652***	21.253**	−0.158	−17.235***	−44.162***	−73.229***
	(3.142)	(2.281)	(1.827)	(1.946)	(3.252)	(9.858)	(5.247)	(2.656)	(4.491)	(9.774)
Read	3.985***	4.949***	5.611***	5.497***	5.340***	−22.355***	−13.228***	−9.896***	−4.831***	0.987
	(1.179)	(0.954)	(0.717)	(0.508)	(0.722)	(2.224)	(1.337)	(1.293)	(1.349)	(2.398)
Christian	−3.487**	−2.362*	−0.169	1.703**	4.366***	−13.896***	−8.071***	−3.928**	3.130	6.969**
	(1.700)	(1.265)	(0.798)	(0.797)	(1.232)	(3.441)	(2.095)	(1.757)	(2.103)	(3.245)
Latitude	0.363**	0.400***	0.370***	0.350***	0.276***	0.730***	0.316**	0.218*	0.130	−0.611
	(0.171)	(0.091)	(0.055)	(0.042)	(0.062)	(0.204)	(0.141)	(0.132)	(0.194)	(0.441)
Rainfall	0.027***	0.029***	0.032***	0.031***	0.033***	−0.089***	−0.058***	−0.058***	−0.046***	−0.035***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.010)	(0.005)	(0.004)	(0.004)	(0.005)
Wetness	0.052***	0.036***	0.035***	0.024***	0.023***	−0.052***	−0.037***	−0.048***	−0.023	0.007
	(0.010)	(0.007)	(0.005)	(0.003)	(0.004)	(0.015)	(0.010)	(0.012)	(0.015)	(0.024)
Dist-Popcenter	0.158***	0.118***	0.079***	0.064***	0.070***	0.067***	0.091***	0.078***	0.083***	0.081**
	(0.017)	(0.010)	(0.008)	(0.006)	(0.006)	(0.025)	(0.017)	(0.019)	(0.024)	(0.042)
Dist-Market	−0.003	−0.005*	−0.008***	−0.010***	−0.021***	−0.024***	−0.024***	−0.024***	−0.029***	−0.054***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.008)	(0.004)	(0.004)	(0.004)	(0.010)
Dist-Border	−0.017***	−0.017***	−0.008	0.003	0.022***	−0.007	−0.047***	−0.040***	−0.059***	−0.085***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.020)	(0.008)	(0.009)	(0.007)	(0.012)
Dist-Capital	−0.059***	−0.040***	−0.034***	−0.021***	−0.018***	0.064***	0.041***	0.063***	0.065***	0.084***
	(0.010)	(0.008)	(0.005)	(0.003)	(0.004)	(0.014)	(0.010)	(0.011)	(0.014)	(0.020)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	12768	12768	12768	12768	12768	12768	12768	12768	12768	12768
Pseudo R-sq	0.340	0.388	0.492	0.546	0.531	0.235	0.296	0.307	0.275	0.252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

$1.17 at the 75th quantile highlighting reduction on the conditional welfare dispersion. For non-food expenditure, the conditional quantile regression effects of credit on non-food expenditure only show positive significant effect at the 25th quantile of $4.67 (this effect is larger than that of food expenditure, which is a notable outcome for the slightly richer countries in this group as compared to low income countries) while other quantiles show no significant effect. This result suggest that when non-food expenditure is considered as a welfare measure in lower-middle income countries, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous, i.e no inequality in welfare outcomes, as there is no significant effect for all quantiles aside the 25th.

Fig. 2 re-enforces the results explained above in a visual way. Fig. 2, shows that the effects of conditional quantile regression of credit is uniformly positive mostly between the low and slightly above median quantiles (education and food expenditure) or uniquely at the 25th quantile (the case for non-food expenditure) and the 25th and 50th quantiles (consumption per capita). Starting from the low quantiles, these effects fall only slightly in magnitude as we move towards the median before the loss of significance at the higher quantiles, as the confidence intervals clearly depicts. The results of the quantile regression on the impact of credit on welfare for the lower-middle income countries suggest that heterogeneity in welfare outcomes is only observed in education and food expenditures while for consumption and non-food expenditures, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous.

We proceed by reporting the result for the low income countries in Tables 10 and 11 along Fig. 3. In this way, we can compare the two sub-samples and examine any similarities or differences between low income and lower-middle income countries, as this is critical and can provide a clearer, country-specific guide (in terms of income levels) for determining who benefits most from micro-credit. The results for the low income countries indicate heterogeneity in welfare outcomes as a result of obtaining credit. Furthermore, these results show that credit significantly affects households that are at low to slightly above median quantiles of the distribution for most welfare indicators.

For the low income countries, from Table 10, we observe that the conditional quantile regression effects of credit on consumption per capita is $29.48 at the 10th quantile, while falls to $22.53 at the median, but loses significance after the 75th quantile. These effects seem to be larger for the low income countries as compared to the lower-middle income countries and suggest that credit shows greater effects for poorer countries. The consistency of this result is seen across consumption per capita and food expenditure, as can be also seen in Fig. 3. However, the conditional quantile regression effects of credit on food expenditure show some interesting results (Table 11). The conditional quantile regression effects of credit on food expenditure initially is $15.30 at the 10th quantile, while it increases to $16.97 and then drops to $10.35 at the median. However, this effect then increases again to $15.34 at the 75th quantile before losing significance at the 90th quantile. Again, these findings strongly confirm the point discussed above that credit has different effects at different levels of the welfare distribution and the conditional quantile regression estimates reported in Tables 10 and 11 show that credit shift the location of the conditional welfare distribution for consumption and food expenditures respectively (i.e., positive effect on the median) but also reduce conditional welfare dispersion.

In terms of education expenditure, we find significant effects only at the extreme low/high quantiles and no effect of credit in all other levels of the welfare distribution when we consider only the low countries. This is observed in both Table 10 and Fig. 3 as opposing signs of the confidence intervals on education indicates that there are no significant effects. This could be because households smooth their credit obtained

Table 10
Panel quantile regressions for consumption and education (Low income countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	29.483***	27.480***	22.539***	15.192*	26.225	1.000***	0.162	−0.031	−0.277	−0.940**
	(5.737)	(3.952)	(4.896)	(8.790)	(16.246)	(0.259)	(0.120)	(0.104)	(0.184)	(0.438)
Male	18.772***	16.734**	18.347***	13.983	−8.314	1.634***	0.360**	−0.432***	−1.228***	−2.580***
	(7.004)	(6.590)	(6.519)	(12.379)	(21.166)	(0.552)	(0.173)	(0.145)	(0.294)	(0.780)
Employed	−19.671**	−12.347**	−5.318	−0.766	−0.608	−2.483***	−0.407***	−0.126	0.354	1.234**
	(8.274)	(5.000)	(5.960)	(8.418)	(23.298)	(0.595)	(0.149)	(0.118)	(0.231)	(0.612)
Married	108.015***	105.309***	118.665***	154.901***	235.069***	1.845***	0.921***	1.187***	1.731***	1.964***
	(8.067)	(6.501)	(6.036)	(11.637)	(21.108)	(0.488)	(0.193)	(0.142)	(0.288)	(0.703)
Read	10.366*	28.165***	52.977***	96.012***	138.511***	−1.784***	−0.343***	0.724***	2.839***	9.164***
	(5.635)	(3.821)	(4.614)	(7.387)	(14.065)	(0.267)	(0.126)	(0.102)	(0.251)	(0.695)
Christian	34.201***	28.193***	21.909***	6.285	−9.535	−1.336***	0.271	0.770***	1.588***	2.343***
	(6.062)	(5.013)	(5.571)	(8.326)	(17.388)	(0.360)	(0.172)	(0.120)	(0.218)	(0.434)
Latitude	72.606***	71.816***	68.777***	65.050***	65.572***	6.433***	5.832***	5.545***	5.047***	4.312***
	(1.752)	(1.365)	(1.653)	(2.400)	(4.866)	(0.093)	(0.063)	(0.044)	(0.072)	(0.116)
Rainfall	−0.143***	−0.166***	−0.201***	−0.252***	−0.318***	−0.006***	−0.006***	−0.006***	−0.007***	−0.009***
	(0.008)	(0.008)	(0.008)	(0.014)	(0.024)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Wetness	−0.484	−0.987	−0.283	−0.774	−4.802	−1.163***	−0.716***	−0.670***	−0.443***	−0.114
	(1.392)	(0.952)	(1.113)	(1.788)	(3.684)	(0.056)	(0.044)	(0.032)	(0.068)	(0.106)
Dist-Popcenter	−0.168**	−0.347***	−0.466***	−0.546***	−0.455**	−0.034***	−0.032***	−0.024***	−0.020***	−0.029***
	(0.083)	(0.076)	(0.078)	(0.121)	(0.222)	(0.003)	(0.002)	(0.002)	(0.003)	(0.007)
Dist-Market	0.960***	0.799***	0.634***	0.399***	0.070	0.037***	0.017***	0.010***	−0.003	−0.026***
	(0.066)	(0.048)	(0.062)	(0.080)	(0.158)	(0.003)	(0.002)	(0.001)	(0.002)	(0.004)
Dist-Border	0.230***	0.198***	0.171***	0.206***	0.254***	0.034***	0.040***	0.042***	0.042***	0.042***
	(0.026)	(0.020)	(0.024)	(0.031)	(0.068)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dist-Capital	0.830***	0.807***	0.776***	0.768***	0.685***	0.056***	0.056***	0.053***	0.051***	0.044***
	(0.023)	(0.017)	(0.018)	(0.028)	(0.049)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	11 442	11 442	11 442	11 442	11 442	11 484	11 484	11 484	11 484	11 484
Pseudo R-sq	0.303	0.292	0.251	0.179	0.119	0.366	0.431	0.428	0.316	0.167

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

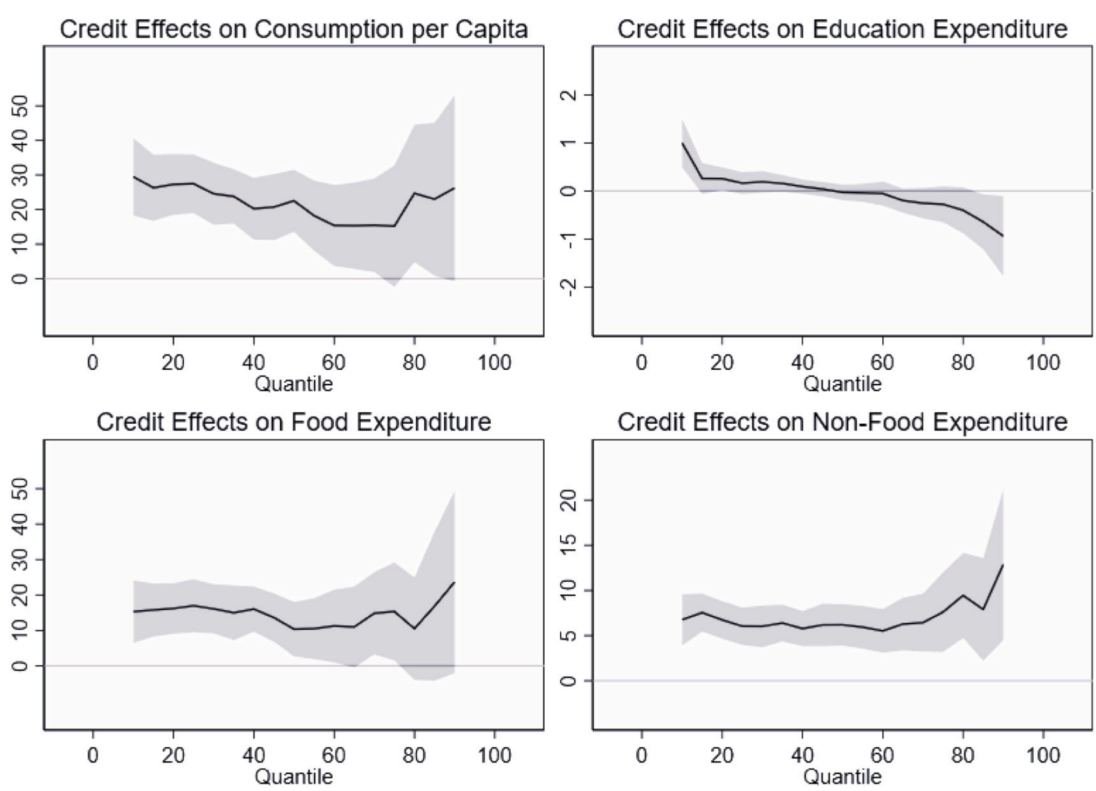

Fig. 3. Quantile regression plots of credit on welfare (Low income countries).

Table 11
Panel quantile regressions for food and non-food expenditures (Low income countries).

Variable	Fd. Exp (Food expenditure)					Non Fd. Exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	15.308***	16.973***	10.354**	15.347**	23.681	6.757***	6.048***	6.199***	7.613***	12.889***
	(4.527)	(3.512)	(4.173)	(6.466)	(15.861)	(1.452)	(1.088)	(1.300)	(2.176)	(3.653)
Male	22.666***	17.336***	21.580***	21.206*	12.768	2.746	1.313	−3.103**	−7.372***	−18.307***
	(5.295)	(4.882)	(5.657)	(11.347)	(17.153)	(1.945)	(1.403)	(1.366)	(2.544)	(5.725)
Employed	−8.386	−5.278	−6.682	−13.684**	−21.202	−4.687**	−4.141***	−2.266	−0.139	5.702
	(5.217)	(4.472)	(4.492)	(6.647)	(15.077)	(1.931)	(1.332)	(1.588)	(2.934)	(5.555)
Married	76.731***	80.375***	93.766***	123.315***	193.976***	19.511***	19.145***	21.013***	26.473***	42.661***
	(6.176)	(5.155)	(5.092)	(11.483)	(14.367)	(1.977)	(1.388)	(1.170)	(2.872)	(5.496)
Read	−3.913	6.556**	23.467***	44.737***	55.055***	4.394***	12.008***	23.403***	41.792***	72.712***
	(4.025)	(2.855)	(3.423)	(5.453)	(10.899)	(1.592)	(0.988)	(1.223)	(2.049)	(4.379)
Christian	15.874***	11.094***	5.766	−13.287*	−10.022	14.391***	11.994***	12.168***	14.033***	19.627***
	(4.960)	(3.518)	(3.744)	(7.572)	(15.023)	(1.832)	(1.272)	(1.285)	(1.918)	(3.634)
Latitude	36.314***	34.404***	33.459***	29.450***	31.348***	32.188***	32.542***	31.595***	30.447***	29.041***
	(1.324)	(1.123)	(1.216)	(1.877)	(3.191)	(0.492)	(0.339)	(0.434)	(0.664)	(1.543)
Rainfall	−0.096***	−0.117***	−0.156***	−0.190***	−0.261***	−0.029***	−0.032***	−0.037***	−0.044***	−0.058***
	(0.008)	(0.007)	(0.008)	(0.012)	(0.021)	(0.002)	(0.001)	(0.002)	(0.004)	(0.007)
Wetness	2.979***	2.257***	0.786	0.412	−4.722*	−2.304***	−2.580***	−2.190***	−1.361***	0.124
	(1.088)	(0.706)	(0.955)	(1.395)	(2.624)	(0.322)	(0.258)	(0.290)	(0.482)	(1.072)
Dist-Popcenter	−0.203***	−0.243***	−0.276***	−0.343***	−0.163	−0.075***	−0.069***	−0.112***	−0.155***	−0.181***
	(0.073)	(0.054)	(0.070)	(0.091)	(0.181)	(0.019)	(0.014)	(0.016)	(0.034)	(0.057)
Dist-Market	0.860***	0.723***	0.519***	0.433***	0.067	0.131***	0.103***	0.080***	0.025	−0.068
	(0.051)	(0.037)	(0.051)	(0.068)	(0.123)	(0.014)	(0.011)	(0.012)	(0.020)	(0.044)
Dist-Border	0.032	−0.028*	−0.050***	−0.023	0.068	0.175***	0.202***	0.189***	0.181***	0.157***
	(0.020)	(0.015)	(0.019)	(0.029)	(0.056)	(0.007)	(0.004)	(0.006)	(0.008)	(0.015)
Dist-Capital	0.408***	0.394***	0.406***	0.375***	0.355***	0.383***	0.371***	0.342***	0.325***	0.319***
	(0.017)	(0.014)	(0.016)	(0.025)	(0.041)	(0.005)	(0.004)	(0.004)	(0.008)	(0.014)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	11 442	11 442	11 442	11 442	11 442	11 442	11 442	11 442	11 442	11 442
Pseudo R-sq	0.224	0.200	0.157	0.110	0.080	0.424	0.432	0.403	0.310	0.211

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 12
Variables with description.

Variable name	Description
Credit	A dummy for households who have applied for and obtained loans where credit = 1 if households obtained the credit and credit = 0, if they do not.
Tot. Cons	Households total consumption per capita (in US Dollars). First indicator for the welfare of households.
Ed. Exp	Household education expenditure (in US Dollars). Second indicator for the welfare of households.
Fd. Exp	Household food expenditure (in US Dollars). Third indicator for the welfare of households.
Non Fd. Exp	Household non-Food expenditure (in US Dollars). Fourth indicator for the welfare of households.
Male	A dummy that equals one if household respondent is male and zero otherwise.
Employed	A dummy that equals one if household has a paid employment and zero otherwise.
Married	A dummy that equals one if household respondent is married and zero otherwise.
Read	A dummy that equals one if households members can read and write and zero otherwise.
Christian	A dummy that equals one if households members are Christians and zero otherwise.
Latitude	Latitude of households, measured by GPS. A measure of household location.
Rainfall	The average yearly rainfall in different household areas.
Wetness	Average start of wettest quarter. A measure of topography and of quality of roads and transportation.
Dist-Popcenter	The distance in kilometres from household to nearest population centre.
Dist-Market	The distance in kilometres from household to the nearest market.
Dist-Border	The distance in kilometres from household to the nearest border.
Dist-Capital	The distance in kilometres from household to the capital of state of residence.

Notes: The dataset is sourced from the World Bank Living Standard Measurement Survey (LSMS) Dataset.

through other welfare measures, as opposed to education, which they may rather see it as a long-term investment, as Table 11 generally indicates. Thus, for low income countries, improving other welfare measures, such as consumption, food, and non-food expenditure is more important to households as compared to education which follows expectation for the less developed countries.

Furthermore, for non-food expenditure, the results in Table 11 indicate heterogeneity in welfare outcomes as a result of obtaining credit similar to Table 7. There are significant effects of credit in all quantile levels across the welfare distribution. At first, the conditional quantile regression effects of credit on non-food expenditure is \$6.75 at the 10th quantile but falls to \$6.19 at the median, after which the effects reverts at the higher quantiles (\$7.61 at the 75th and increases to \$12.88 at the 90th quantile) thus widening the conditional welfare dispersion in non-food expenditure suggesting that credit has different effect on non food expenditure for the low quantiles in the welfare distribution as opposed to the higher quantiles. For both extreme quantiles (low and high), the conditional quantile regression estimates reported in Table 11 show that credit shift the location of the conditional welfare distribution but reduces conditional welfare dispersion for the lower quantiles as opposed to the increase in the conditional welfare dispersion for richer households. Moreover, while poorer households are more interested on meeting basic needs like food, only richer households can really spend much more on non-food expenditures in low income countries.

Table 13
Controls and determinants of welfare (Alternative specification).

	Tot. cons	Ed. exp	Fd. exp	Non fd. exp
Male	7.708	2.515	14.41*	11.81*
	(8.540)	(2.510)	(6.228)	(5.079)
Employed	23.60***	−17.75***	5.903	−11.02***
	(6.132)	(1.551)	(4.146)	(3.274)
Married	64.98***	−5.160*	48.03***	−17.83***
	(8.163)	(2.408)	(5.906)	(4.823)
Read	88.71***	7.258***	34.02***	32.08***
	(5.288)	(1.572)	(3.770)	(3.138)
Christian	−8.192	9.092***	−19.80***	25.34***
	(5.447)	(2.583)	(3.965)	(4.256)
Latitude	−2.214***	−0.0102	−1.436**	−1.726***
	(0.634)	(0.212)	(0.461)	(0.416)
Wetness	0.0562	0.0792***	0.0160	0.113***
	(1.072)	(0.00415)	(0.0110)	(0.00866)
Dist-Market	−0.0262	0.0290***	−0.00693	−0.0446***
	(0.0148)	(0.00435)	(0.0104)	(0.00858)
Group FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	20 238	24 307	24 265	24 265

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Although the main objective of this paper is to examine the effects of credit across the various distribution of welfare measures in both low and lower-middle income African countries, we would like to highlight the impact of several of the controls used in the study across the various quantiles. The results indicate that being male, employed, literate, Christian, and married impacts positively welfare across various quantiles for most welfare indicators. Conversely, distance to the market, border, capital, and population centre affects negatively welfare for most welfare indicators. However, the sign of these effects, especially for the distance to capital and distance to population centre, varies when we compare the results by income levels of countries, that is lower-middle income countries and low income countries. For lower-middle income countries, the effect of distance to population centre on consumption for instance is heterogeneous and ranges from positive to negative effects but for low income countries, this effect is mostly negative.

Furthermore, the effect of rainfall and wetness of land on welfare is heterogeneous across the various quantiles and varies by both the welfare indicator concerned and the income level of the country. Also, the results show a positive effect of rainfall and wetness of land on food expenditure and consumption per capita for lower-middle income countries, while the reverse (negative and significant) is the case for low income countries, especially for rainfall. Again, this could relate to the fact that richer countries are more productive than the poorer ones with poorer countries having many of their population concentrated in rural areas were productivity is lower. However, we find negative effects of rainfall and wetness of land on education and non-food expenditure and these effects are consistent across both lower-middle and low income countries. Interestingly, latitude also show positive effects across the various quantiles irrespective of the income category of the countries included.

5.4. Robustness checks

To ensure that the results obtained in the study are robust, we employ a variety of checks. First, we re-estimate various specifications of the regression, using the Machado and Santos Silva (2019) method, without additional controls (outside of credit) while including group, country and time fixed effects both individually and collectively, as seen in Tables 14 and 15 of the Appendix. The results reinforce the findings of our main analysis that there are inequalities in welfare outcomes from obtaining credit. Any significant effects are particular to households that are at the low to median quantiles of the distribution for most part.

Next, we change the empirical specification, using both the Machado and Santos Silva (2019) and the modified (Canay, 2011) methods, by employing an alternative (reduced) specification over the controls used in Table 3. Controls such as distance to border, population centre, capital and rainfall are excluded to explore the robustness of the effect of credit on welfare in the absence (or inclusion) of these controls, see Table 13 in the Appendix for the full list of controls used in this specification.[9] The results of this new specification are reported in Tables 16 to 17 (using the Machado & Santos Silva, 2019 estimator) and Tables 18 to 19 (using the modified Canay, 2011 estimator) for all countries, as well as in Tables 20 to 23 for the sub-sample analysis, see Appendix. Using this alternative (reduced) specification with both estimators, we find that the results remain mostly unchanged and align with those reported in the main and complementary analyses for all countries as well as for the sub-sample analysis. This reaffirms our main finding that the effect of credit is highly heterogeneous, with substantial impacts in countries with low welfare levels compared to wealthier ones with similar characteristics, while the impact is minimal in countries with relatively high welfare levels.

What the results suggest is that obtaining credit is crucial for households from low to (slightly above) median levels of the distribution of welfare as regards consumption per capita and food expenditure. Thus, obtaining micro-credit improves the welfare (in terms of consumption per capita and food expenditure) of households at the low and median quantiles when we consider both low and lower-middle African countries together. However, one can observe a shift in location from low to median quantiles of this effect. That is as the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure falls until the median quantile, after which there is no statistical significance of the effect. For education and non-food expenditures, we find similar results with those reported in Tables 4 and 5. For education expenditure, there are no significant effect of credit at all quantiles on the welfare distribution when one considers only the low income countries while for non-food expenditure, the results show heterogeneity in welfare outcomes as a result of obtaining credit. We find a significant effect in all quantile levels across the welfare distribution which also strongly confirms the point discussed above that credit has different effects at different points of the welfare distribution. These effects also show a mixed pattern of reduction in the conditional welfare dispersion from low to median quantiles and then reverts to increase in the conditional welfare dispersion at the higher quantiles which have been clearly noted in Tables 4 and 5.

6. Conclusions and policy recommendations

This paper employs a panel quantile regression framework to analyse the welfare effects of credit across varying levels of household welfare distribution. The results from the panel quantile estimation suggest that there is heterogeneity in the welfare outcomes of households as a result of obtaining credit. However, the significant effects are particular to households that are at the low to median quantiles of the distribution. This conclusion is consistent across the combination of low income and lower-middle income countries as well as for the group of low income countries. Thus, an important implication to draw from this result is that if governments and development organisation intend to

[9] The same is also done for various combinations of our controls, but similar outcomes are found. Furthermore, we employ an additional specification, using the modified (Canay, 2011) estimator, where we include credit in lagged form to check whether credit has a longer lasting impact on welfare. We find similar results with those presented in Section 5.1. These additional results are available upon request.

Table 14
Robustness: Alternative panel quantile regression estimates (All countries).

τ	Tot. cons (Consumption per capita)				Ed. exp (Education expenditure)			
0.1	31.98***	15.31***	19.22***	33.67***	1.188	1.860**	2.178***	0.692
	(5.249)	(3.206)	(3.387)	(5.217)	(0.769)	(0.769)	(0.714)	(0.750)
0.25	31.50***	13.61***	14.77***	33.06***	1.717*	1.965***	1.924***	0.627
	(4.805)	(2.744)	(2.561)	(4.622)	(1.037)	(0.374)	(0.3873)	(1.123)
0.5	28.15***	7.101*	10.73***	29.45***	2.210*	2.045***	1.673***	0.504
	(6.518)	(3.653)	(3.303)	(5.941)	(1.175)	(0.446)	(0.412)	(1.275)
0.75	20.88	−3.21	1.840	21.84	3.705	2.337	0.722	0.179
	(14.64)	(7.681)	(6.996)	(14.040)	(2.748)	(1.519)	(1.421)	(2.448)
0.9	20.66	−17.47	−11.81	21.46	4.595	2.981	−1.584	0.0470
	(15.292)	(14.373)	(14.308)	(14.708)	(3.597)	(3.722)	(3.541)	(3.113)
Group FE	Yes	No	No	Yes	Yes	No	No	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 15
Robustness: Alternative panel quantile regression estimates (All countries).

τ	Fd. exp (Food expenditure)				Non fd. exp (Non-food expenditure)			
0.1	14.60***	6.029***	8.115***	18.231***	6.957***	11.47***	9.988***	6.181***
	(2.665)	(1.993)	(2.548)	(3.031)	(1.866)	(1.624)	(1.656)	(1.429)
0.25	13.56***	2.791	3.661	17.10***	8.190***	9.809***	8.048***	6.518***
	(3.167)	(2.051)	(2.380)	(3.275)	(1.872)	(1.160)	(1.027)	(1.670)
0.5	13.19***	2.786	−0.985	13.955***	10.16***	6.325***	4.426***	7.050***
	(3.042)	(2.157)	(2.369)	(4.852)	(3.077)	(1.498)	(1.436)	(2.631)
0.75	7.135	−10.60	−2.146	9.481	13.34***	0.656	−2.103	8.193*
	(11.726)	(6.502)	(4.376)	(10.249)	(4.960)	(4.183)	(3.942)	(4.77)
0.9	5.298	−26.04	−13.13*	7.827	15.12**	−8.628	−12.74*	8.925
	(14.907)	(14.50)	(6.750)	(13.011)	(6.448)	(7.142)	(7.235)	(6.503)
Group FE	Yes	No	No	Yes	Yes	No	No	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 16
Robustness: Alternative panel quantile regressions for consumption and education (All countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	17.861***	16.628***	12.612*	4.279	2.444	1.761**	1.553	1.159	0.128	−0.344
	(5.461)	(5.151)	(6.930)	(14.880)	(16.987)	(0.802)	(1.056)	(1.226)	(2.276)	(3.213)
Male	8.877	10.855	17.296*	30.661	33.603	1.882*	2.044**	2.351**	3.154	3.521
	(10.773)	(6.984)	(9.531)	(21.547)	(23.010)	(1.061)	(0.994)	(1.024)	(3.312)	(3.282)
Employed	5.651	4.929	2.578	−2.298	−3.372	−19.615***	−19.219***	−18.469***	−16.505***	−15.607***
	(5.504)	(5.593)	(6.352)	(16.361)	(20.464)	(2.521)	(2.351)	(2.108)	(2.229)	(2.034)
Married	94.857***	107.816***	150.014***	237.565***	256.843***	−1.429	−1.626	−2.000	−2.978	−3.425
	(10.052)	(9.922)	(12.173)	(25.388)	(28.598)	(1.155)	(1.119)	(1.266)	(2.991)	(2.984)
Read	43.516***	45.633***	52.525***	66.826***	69.975***	−1.153**	−0.132	1.807**	6.876***	9.193***
	(5.067)	(4.943)	(6.999)	(11.626)	(14.658)	(0.450)	(0.408)	(0.749)	(1.606)	(2.107)
Christian	8.314	9.746	14.407	24.079	26.208	1.098	1.193**	1.374	1.846	2.062
	(9.581)	(8.786)	(13.596)	(30.342)	(33.798)	(0.934)	(0.591)	(1.958)	(4.981)	(7.348)
Latitude	1.619***	1.633***	1.676***	1.766***	1.785***	0.388**	0.404**	0.434**	0.514**	0.550**
	(0.267)	(0.254)	(0.301)	(0.392)	(0.507)	(0.179)	(0.171)	(0.202)	(0.255)	(0.261)
Wetness	1.199	1.353	1.853	2.892	3.120	0.062***	0.065***	0.072***	0.089***	0.097***
	(2.169)	(2.375)	(3.154)	(6.788)	(7.312)	(0.005)	(0.006)	(0.006)	(0.011)	(0.012)
Dist-Market	−0.048***	−0.046***	−0.041**	−0.031	−0.029	0.041***	0.038***	0.033***	0.019***	0.013**
	(0.012)	(0.013)	(0.016)	(0.031)	(0.031)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 17
Robustness: Alternative panel quantile regressions for food and non-food expenditures (All countries).

Variable	Fd. exp (Food expenditure)					Non fd. exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	8.985***	7.652**	4.819	−0.034	−2.649	4.526***	4.775***	5.257*	6.146	6.686
	(2.762)	(3.184)	(5.695)	(11.714)	(14.088)	(1.491)	(1.433)	(2.841)	(5.514)	(7.855)
Male	17.126**	22.728***	34.630***	55.018***	66.006***	−0.260	0.588	2.229	5.259	7.097
	(6.747)	(5.779)	(7.658)	(17.184)	(20.149)	(2.336)	(2.690)	(3.872)	(7.257)	(10.277)
Employed	6.627**	5.773**	3.959	0.852	−0.823	−7.771***	−7.967***	−8.347***	−9.049*	−9.475
	(2.669)	(2.490)	(3.951)	(9.908)	(10.950)	(2.442)	(2.362)	(2.895)	(4.786)	(6.594)
Married	58.385***	73.771***	106.455***	162.442***	192.616***	12.160***	15.956***	23.303***	36.864***	45.093***
	(6.537)	(6.497)	(10.225)	(19.342)	(23.876)	(2.620)	(3.455)	(5.052)	(9.410)	(13.478)
Read	18.924***	18.725***	18.301***	17.575*	17.183	11.093***	14.773***	21.896***	35.044***	43.023***
	(3.252)	(3.895)	(5.144)	(9.252)	(13.290)	(1.651)	(1.540)	(1.919)	(4.319)	(6.306)
Christian	−9.824	−6.995	−0.986	9.308	14.856	7.696	9.948**	14.308***	22.354***	27.237***
	(10.507)	(8.779)	(11.599)	(21.277)	(28.800)	(4.867)	(4.490)	(4.726)	(8.091)	(10.035)
Latitude	0.583***	0.575***	0.557***	0.527***	0.510***	−0.397	−0.293	−0.091	0.281	0.506
	(0.119)	(0.127)	(0.123)	(0.147)	(0.195)	(0.330)	(0.329)	(0.479)	(0.678)	(0.740)
Wetness	−0.022***	−0.021***	−0.021***	−0.020***	−0.020***	0.069***	0.078***	0.097***	0.131***	0.152***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)	(0.011)	(0.012)	(0.024)	(0.026)
Dist-Market	−0.017***	−0.017***	−0.017***	−0.017**	−0.017	−0.019	−0.023*	−0.030**	−0.044***	−0.053***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.011)	(0.013)	(0.012)	(0.013)	(0.016)	(0.017)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the quantiles via moments estimator of Machado and Santos Silva (2019) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 18
Robustness: Alternative panel quantile regressions for consumption and education (All countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	17.141***	12.774***	10.584***	8.229***	11.208***	1.204***	0.534***	0.323**	0.427*	−0.302
	(2.854)	(2.126)	(1.642)	(2.126)	(4.170)	(0.289)	(0.169)	(0.149)	(0.253)	(0.555)
Male	21.709***	23.241***	21.224***	26.144***	26.540***	1.425**	0.267	−0.276	−0.502	−1.055
	(5.545)	(4.011)	(1.983)	(3.763)	(9.151)	(0.704)	(0.260)	(0.192)	(0.407)	(0.886)
Employed	1.533	1.197	5.576***	5.792***	6.493**	−8.330***	−6.655***	−4.202***	−4.334***	−5.356***
	(3.462)	(1.932)	(1.715)	(1.858)	(2.549)	(0.961)	(0.386)	(0.220)	(0.228)	(0.549)
Married	167.472***	155.074***	163.684***	161.416***	166.529***	3.835***	1.500***	0.903***	−0.322	−3.617***
	(5.019)	(3.492)	(1.938)	(3.872)	(8.664)	(1.039)	(0.253)	(0.200)	(0.436)	(1.211)
Read	31.694***	39.354***	48.865***	55.522***	61.385***	−3.664***	−0.622***	0.848***	3.151***	10.213***
	(2.108)	(1.621)	(1.417)	(1.497)	(2.547)	(0.321)	(0.175)	(0.163)	(0.246)	(0.656)
Christian	18.819***	16.605***	16.025***	15.796***	17.141***	−1.460***	0.761***	1.741***	3.750***	6.989***
	(2.249)	(2.129)	(1.642)	(2.147)	(4.427)	(0.306)	(0.171)	(0.162)	(0.217)	(0.490)
Latitude	2.668***	1.890***	1.422***	1.041***	0.706***	1.045***	0.493***	0.262***	−0.036	−0.375***
	(0.230)	(0.173)	(0.099)	(0.111)	(0.112)	(0.062)	(0.032)	(0.021)	(0.035)	(0.080)
Wetness	2.814***	3.257***	2.138***	1.062	0.884	0.042***	0.042***	0.055***	0.090***	0.159***
	(0.725)	(0.528)	(0.366)	(0.677)	(1.092)	(0.001)	(0.001)	(0.002)	(0.005)	(0.010)
Dist-Market	−0.047***	−0.038***	−0.033***	−0.034***	−0.034***	0.019***	0.023***	0.031***	0.032***	0.033***
	(0.009)	(0.005)	(0.003)	(0.004)	(0.006)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252
Pseudo R-sq	0.267	0.259	0.220	0.164	0.173	0.161	0.258	0.406	0.435	0.400

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

improve the welfare of households through financial credit programs, then the credit recipients should be those in low and median level households. Generally, for Sub-Saharan African countries, financial credit policies are most impactful for poorer households as compared to the richer ones in regards of the welfare level. This conclusion is also persistent if one considers only low income countries.

However, for welfare indicators that are more realisable after longer periods, e.g., education, only low to the median welfare level households in lower-middle income countries and low welfare households in low income countries show positive effects. Generally, policy makers can target households at the median or below median level households in lower-middle to raise welfare standards in lower-middle income countries especially as regards consumption per capita, food, education and non-food welfare measures. For low income countries, poor households tend to smooth their income across other welfare indicators that they consider could raise their standard of living at shorter basis and not the long-term indicators.

In summary, we recommend that for Sub-Saharan African countries, governments and policy makers should consider low to median level welfare households as regards micro-credit policies aimed at improving welfare levels. For low income countries in isolation, governments and policy makers should consider for the most part low to slightly above median welfare level households to raise welfare levels especially for welfare indicators that are most realisable in the short-run e.g., consumption per capita and food/non-food welfare indicators. For lower-middle income countries alone, policy makers can consider

Table 19
Robustness: Alternative panel quantile regressions for food and non-food expenditures (All countries).

Variable	Fd. exp (Food expenditure)					Non fd. exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	8.113***	7.616***	3.730***	2.432**	1.017	7.281***	5.659***	4.913***	5.200***	8.600***
	(1.606)	(1.878)	(1.046)	(1.101)	(1.119)	(2.029)	(1.051)	(1.033)	(1.631)	(3.335)
Male	41.125***	42.661***	43.101***	57.806***	70.868***	1.249	3.758**	2.360	3.287	7.377
	(4.141)	(2.590)	(1.527)	(4.614)	(4.281)	(2.846)	(1.474)	(1.449)	(2.287)	(4.678)
Employed	7.827***	6.093***	6.605***	5.888***	4.202***	−8.338***	−7.438***	−5.407***	−6.444***	−9.055***
	(1.942)	(1.100)	(0.643)	(0.716)	(0.835)	(1.894)	(0.981)	(0.964)	(1.522)	(3.113)
Married	113.544***	105.315***	103.558***	95.775***	82.710***	37.280***	26.379***	21.221***	14.906***	5.687
	(4.405)	(2.960)	(1.273)	(4.580)	(4.627)	(2.700)	(1.398)	(1.375)	(2.170)	(4.438)
Read	6.356***	11.286***	14.413***	15.991***	14.979***	4.498***	11.981***	19.629***	30.107***	44.255***
	(1.355)	(0.827)	(0.791)	(0.654)	(0.852)	(1.722)	(0.892)	(0.877)	(1.384)	(2.831)
Christian	−0.251	−0.180	0.684	0.538	1.210	12.642***	13.527***	13.113***	17.422***	23.106***
	(1.120)	(1.322)	(0.639)	(1.235)	(1.899)	(1.818)	(0.942)	(0.926)	(1.461)	(2.989)
Latitude	0.958***	0.777***	0.475***	0.259***	0.204***	0.448**	0.275**	−0.065	−0.109	−0.289
	(0.147)	(0.091)	(0.049)	(0.056)	(0.051)	(0.211)	(0.109)	(0.107)	(0.169)	(0.346)
Wetness	−0.035***	−0.025***	−0.019***	−0.015***	−0.014***	0.052***	0.054***	0.069***	0.102***	0.165***
	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(0.003)	(0.004)	(0.008)
Dist-Market	−0.017***	−0.021***	−0.018***	−0.015***	−0.016***	−0.015***	−0.007***	−0.005**	−0.008**	−0.037***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.008)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210
Pseudo R-sq	0.283	0.276	0.213	0.196	0.216	0.203	0.317	0.384	0.335	0.252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 20
Robustness: Alternative panel quantile regressions for consumption and education (Lower-middle income countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	2.731	4.523**	2.151	3.028**	−0.585	2.952*	2.548***	2.279***	2.516**	2.250
	(2.406)	(2.172)	(1.498)	(1.377)	(2.731)	(1.619)	(0.840)	(0.835)	(1.017)	(1.735)
Male	31.688***	46.043***	51.004***	57.709***	80.057***	−22.958***	−24.595***	−22.427***	−15.875***	−13.782***
	(6.791)	(5.014)	(1.830)	(2.725)	(6.291)	(4.565)	(2.166)	(1.588)	(3.030)	(4.318)
Employed	19.818***	18.099***	21.579***	20.447***	18.023***	−17.122***	−18.957***	−18.542***	−21.108***	−24.373***
	(2.440)	(1.896)	(1.645)	(1.095)	(1.534)	(1.198)	(0.630)	(0.648)	(0.760)	(1.630)
Married	22.412***	7.580	−0.581	−11.196***	−37.756***	−12.931***	−22.395***	−29.379***	−40.855***	−46.285***
	(6.687)	(5.050)	(0.529)	(2.765)	(6.699)	(3.708)	(2.299)	(1.444)	(2.819)	(4.721)
Christian	−11.725***	−6.362***	−0.143	2.799*	9.281***	−15.771***	−4.840***	1.685**	8.626***	16.798***
	(2.066)	(1.745)	(0.615)	(1.587)	(3.130)	(2.232)	(0.929)	(0.844)	(0.818)	(1.791)
Read	11.885***	14.084***	14.854***	14.569***	16.137***	−16.281***	−9.996***	−5.189***	−1.782***	3.152***
	(1.879)	(1.704)	(1.031)	(1.151)	(1.442)	(1.321)	(0.600)	(0.632)	(0.583)	(1.185)
Latitude	2.219***	1.562***	1.314***	0.865***	0.708***	0.995***	0.549***	0.297***	0.051	−0.204**
	(0.277)	(0.134)	(0.085)	(0.063)	(0.087)	(0.090)	(0.052)	(0.042)	(0.040)	(0.102)
Wetness	2.537***	2.825***	1.136***	0.407	−0.544	0.054***	0.048***	0.052***	0.081***	0.140***
	(0.738)	(0.540)	(0.221)	(0.532)	(0.886)	(0.002)	(0.001)	(0.002)	(0.004)	(0.009)
Dist-Market	−0.062***	−0.046***	−0.041***	−0.038***	−0.043***	0.023***	0.024***	0.027***	0.026***	0.033***
	(0.008)	(0.005)	(0.002)	(0.003)	(0.005)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252
Pseudo R-sq	0.267	0.259	0.220	0.164	0.173	0.161	0.258	0.406	0.435	0.400

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 21
Robustness: Alternative panel quantile regressions for food and non-food expenditures (Lower-middle income countries).

Variable	Fd. exp (Food expenditure)					Non fd. exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	0.971	1.927*	1.846*	1.300***	0.283	5.779	3.397*	−0.026	0.270	−1.784
	(1.816)	(1.056)	(0.968)	(0.423)	(0.896)	(4.472)	(1.916)	(1.764)	(2.400)	(4.906)
Male	−19.225***	−8.969***	−3.509	−1.350	5.316	−61.372***	−55.271***	−48.845***	−37.696***	−25.326***
	(3.584)	(2.269)	(2.206)	(1.717)	(3.750)	(6.805)	(2.915)	(2.684)	(3.653)	(7.467)
Employed	13.824***	12.022***	12.022***	10.154***	8.344***	−10.640***	−11.060***	−10.018***	−12.841***	−16.273***
	(1.303)	(0.640)	(0.717)	(0.548)	(0.872)	(3.487)	(1.494)	(1.376)	(1.872)	(3.826)
Married	9.046***	−7.603***	−15.954***	−20.972***	−29.163***	25.711***	−0.188	−17.299***	−45.034***	−69.743***
	(3.253)	(2.191)	(1.837)	(1.291)	(4.394)	(6.004)	(2.572)	(2.368)	(3.223)	(6.588)
Read	3.196**	4.486***	4.839***	4.900***	4.486***	−20.393***	−10.263***	−7.517***	−1.648	2.828
	(1.425)	(1.018)	(0.891)	(0.674)	(0.693)	(3.588)	(1.537)	(1.415)	(1.926)	(3.937)
Christian	−7.594***	−4.703***	0.021	1.852***	5.151***	−14.611***	−8.010***	−4.242***	5.778***	10.348**
	(1.038)	(1.019)	(0.655)	(0.707)	(1.582)	(3.966)	(1.699)	(1.565)	(2.129)	(4.352)
Latitude	0.764***	0.570***	0.445***	0.353***	0.256***	0.737**	0.326**	0.093	0.085	−0.618
	(0.139)	(0.074)	(0.038)	(0.050)	(0.082)	(0.349)	(0.149)	(0.138)	(0.187)	(0.383)
Wetness	−0.021***	−0.020***	−0.017***	−0.017***	−0.017***	0.063***	0.061***	0.073***	0.101***	0.164***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.008)	(0.003)	(0.003)	(0.004)	(0.008)
Dist-Market	−0.021***	−0.021***	−0.018***	−0.018***	−0.022***	−0.011	−0.004	−0.001	−0.005	−0.031***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)	(0.007)	(0.003)	(0.003)	(0.004)	(0.008)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210
Pseudo R-sq	0.283	0.276	0.213	0.196	0.216	0.203	0.317	0.384	0.335	0.252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

Table 22
Robustness: Alternative panel quantile regressions for consumption and education (Low income countries).

Variable	Tot. cons (Consumption per capita)					Ed. exp (Education expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	28.450***	25.872***	19.686***	17.891**	26.074	0.667***	0.131	0.144	−0.130	−0.720**
	(5.105)	(3.798)	(4.647)	(8.603)	(17.142)	(0.181)	(0.120)	(0.108)	(0.167)	(0.364)
Male	22.327***	16.555***	17.683***	11.330	−14.221	1.665***	0.227	−0.429***	−1.164***	−2.591***
	(5.640)	(6.298)	(6.624)	(11.705)	(21.554)	(0.401)	(0.159)	(0.150)	(0.285)	(0.749)
Employed	−17.618***	−16.184***	−6.308	−7.643	−9.008	−2.123***	−0.392***	0.010	0.326*	1.025*
	(6.571)	(5.489)	(5.504)	(8.633)	(23.354)	(0.560)	(0.139)	(0.124)	(0.175)	(0.589)
Married	114.289***	108.160***	120.535***	158.910***	230.587***	1.555***	1.015***	1.159***	1.641***	1.925***
	(6.515)	(6.281)	(6.458)	(11.489)	(20.714)	(0.328)	(0.179)	(0.160)	(0.282)	(0.729)
Read	8.831**	23.911***	55.775***	100.027***	141.214***	−1.390***	0.054	0.971***	2.914***	9.596***
	(4.358)	(3.662)	(5.077)	(7.216)	(13.684)	(0.192)	(0.111)	(0.088)	(0.234)	(0.747)
Christian	44.419***	35.938***	21.655***	4.374	−28.258**	−0.997***	0.841***	1.023***	1.357***	2.498***
	(5.495)	(4.063)	(5.078)	(7.319)	(14.172)	(0.238)	(0.123)	(0.116)	(0.207)	(0.448)
Latitude	36.310***	36.152***	34.311***	33.529***	36.846***	4.104***	3.432***	3.145***	2.791***	2.133***
	(1.523)	(1.272)	(1.424)	(2.481)	(4.642)	(0.073)	(0.047)	(0.034)	(0.059)	(0.117)
Wetness	2.207*	1.913**	1.973*	1.049	−3.040	−0.568***	−0.183***	−0.193***	−0.037	0.296***
	(1.191)	(0.775)	(1.091)	(1.874)	(3.506)	(0.047)	(0.036)	(0.027)	(0.049)	(0.102)
Dist-Market	0.793***	0.552***	0.401***	0.188***	−0.063	0.028***	0.010***	−0.002**	−0.017***	−0.042***
	(0.056)	(0.036)	(0.048)	(0.068)	(0.136)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20 183	20 183	20 183	20 183	20 183	24 252	24 252	24 252	24 252	24 252
Pseudo R-sq	0.267	0.259	0.220	0.164	0.173	0.161	0.258	0.406	0.435	0.400

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

households at median welfare level and slightly below median welfare levels to raise welfare. Credit policies also improve the welfare levels of these households for indicators, such as education, because they are more exposed to development and the need for education as compared to low income countries. Alternatively, credit in the form of tuition vouchers, tuition receipts and scholarships could be considered rather than giving out loans in monetary forms to poor households. This is because, for these households, meeting immediate needs is prioritised over needs that are rather seen as for the future such as education. These needs are more towards improving other welfare measures as consumption and food/non-food expenditures which they perceive to be more immediate and short-termed than education.

An area for future research could be the exploration of the link between credit, entrepreneurship, and welfare using panel data and quantile methods. This approach could facilitate the examination of various proxies for entrepreneurship that may influence the relationship between credit and welfare. Although some welfare measures used here, such as food expenditure, are expected to alleviate poverty and

Table 23
Robustness: Alternative panel quantile regressions for food and non-food expenditures (Low income countries).

Variable	Fd. exp (Food expenditure)					Non fd. exp (Non-food expenditure)				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	20.353***	18.984***	10.445***	12.909**	17.327	8.757***	6.377***	6.140***	7.938***	14.552***
	(4.659)	(3.634)	(3.978)	(6.552)	(15.688)	(1.411)	(1.115)	(1.128)	(1.874)	(4.048)
Male	22.531***	19.481***	23.276***	22.862*	7.442	2.578	0.216	−1.446	−8.018***	−15.927***
	(5.849)	(5.202)	(5.415)	(12.374)	(19.380)	(2.102)	(1.255)	(1.500)	(2.505)	(5.065)
Employed	−13.008**	−8.378**	−10.237**	−12.304**	−20.938	−7.244***	−5.159***	−2.746*	0.890	5.906
	(5.256)	(4.236)	(4.413)	(6.277)	(15.942)	(2.133)	(1.386)	(1.492)	(2.623)	(5.155)
Married	82.846***	80.087***	91.794***	124.754***	196.107***	21.279***	20.147***	19.616***	26.569***	40.653***
	(6.420)	(4.925)	(4.952)	(11.826)	(16.773)	(1.988)	(1.352)	(1.256)	(2.650)	(4.573)
Read	−5.337	6.060**	21.144***	43.785***	60.463***	6.257***	13.273***	24.232***	42.933***	72.851***
	(4.135)	(2.843)	(3.557)	(5.865)	(11.584)	(1.296)	(1.167)	(1.267)	(2.002)	(4.386)
Christian	27.830***	18.500***	2.936	−18.622***	−27.250**	17.068***	14.907***	11.798***	13.089***	14.827***
	(4.478)	(3.008)	(4.089)	(5.774)	(13.838)	(1.340)	(1.100)	(1.163)	(1.614)	(3.263)
latitude	15.798***	15.312***	15.949***	13.216***	15.782***	16.512***	16.619***	17.154***	16.823***	16.388***
	(1.254)	(1.019)	(1.147)	(1.867)	(3.555)	(0.418)	(0.299)	(0.405)	(0.607)	(1.341)
Wetness	3.251***	2.874***	1.770*	0.894	−2.616	−0.154	−0.285	−0.729***	−0.415	1.149
	(1.045)	(0.779)	(0.983)	(1.461)	(2.767)	(0.320)	(0.203)	(0.268)	(0.439)	(0.990)
Dist-Market	0.647***	0.518***	0.390***	0.297***	0.068	0.104***	0.069***	0.022**	−0.045**	−0.108***
	(0.048)	(0.033)	(0.036)	(0.055)	(0.118)	(0.012)	(0.010)	(0.010)	(0.018)	(0.039)
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210	24 210
Pseudo R-sq	0.283	0.276	0.213	0.196	0.216	0.203	0.317	0.384	0.335	0.252

Notes: Standard errors are reported in brackets and *, **, *** represent 10, 5 and 1 percent significance levels respectively. The estimates are based on the modified 2-step quantile estimator of Canay (2011) with standard errors based on 100 bootstrapped samples. We include group, country and time fixed effects collectively to control for any other group, country and time invariant unobservable factors in the estimation.

hunger, they do not capture all aspects of welfare. Measures such as health outcomes and subjective well-being could be considered in future work to provide a broader perspective on welfare impacts. Additionally, given the limitations in data availability during and after the Covid-19 period, we recommend future research into the relationship between credit flows and household welfare in Sub-Saharan Africa, while accounting for the pandemic's impact on the financial activities of households and banks. Experimental or quasi-experimental impact evaluation methods would be particularly valuable in this context.

CRediT authorship contribution statement

Emmanuel O. James: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dimitrios Bakas:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization. **Piers Thompson:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization. **John Ebireri:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Tables 12–23.

Data availability

Data will be made available on request.

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